Master thesis for the Master of Environmental and Development Economics

Structural Time Series Models: theory and application

GDP time series in USA, Euro-area, GBR, Sweden and Japan

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Preface

Studying a new model is not always an easy task. Especially, when it comes with a new program, new concepts and at the same time, growing recognition of lack of knowledge. It has been quite a long time since I started to read for this thesis, and I am about to finish it. Even though I am finishing it now, I know that I have just explored a tiny bit of 'Structural time series', and there are a lot to study more. It has been interesting to learn and I am glad that I could get the chance to write this thesis.

I would like to thank Dr. Dag Kolsrud at the research department, Statistics Norway, for his grateful supports and encouraging comments through whole period of the thesis. He gave me the opportunity to write the thesis in the first place, and helped me to learn from the very beginning of the process.

I also would like to thank my supervisor, Professor Ragnar Nymoen for his comments with full knowledge and expertise. He showed me a broad view of the time series models, and encouraged me to enlarge my ideas within the subject.

Lastly, I specially thank my husband, Rune Nakstad for his endless support and motivation. He has been all the time on my side through the whole study time. Without him, I could not have even started the master program, and of course, could not have been here right now.

All errors are the responsibility of the author.

Yoon Shin Nakstad

21. 08. 2006

Executive summary

This thesis studies structural time series model (STM) and its application. A STM decomposes a time series into a trend (level plus slope), a cycle, a seasonal and an irregular component. The model is estimated by the Kalman filter, and we can interpret each component directly. In this thesis, we build structural models with real GDP time series in USA, EURO-area, GBR, Sweden and Japan. We decompose the GDP time series with a smooth trend (fixed level plus stochastic slope), and we focus on the trend and the cyclical component.

The central question in an univariate modelling process is how stochastic the trend should be. When the trend is so stochastic that it matches almost to the actual series, the cycle will have very small disturbance variance. In this case, the cycle will be too short and have no useful information. As a result, the model's forecast will be poor. If the trend is not stochastic such as a deterministic trend, the model will generate an inappropriate cycle with fairly long cycle's length and high amplitude. Consequently, we have to balance between the trend and the cycle. During the univariate modelling process, we find out that the intervention may play an important role to decide how stochastic the trend should be in a STM. We witness this with the USA, GBR, Swedish and Japanese GDP time series. We experiment the models by applying different set of interventions, and present them as alternative models.

We have studied the forecasts of each univariate model. In STM, we obtain each components' forecasts separately, and they are directly interpretable. However, it may lead us to misunderstand the forecasts, if we only look into the cycle forecast. A STM forecasts both trend and cycle, thus we should refer both trend and cycle for forecasting. For doing this, we suggest to use the forecasted growth rate. This shows the sum growth rates of both trend and cycle. We compare the forecasted growth rates with the growth rate projections of OECD (2005, Economic Outlook No.78). All the univariate models show similar growth rate patterns to the one of OECD.

One of advantages of STM is the capability of modelling multivariate models. Globalisation has caused closer economic relationships among countries. Many countries are connected economically, and as a result, one event in a country can affect greatly on other countries'

economy. In this incident, the multivariate model will give appropriate information about how the countries move together under each other's effects and STM is a useful tool for this.

Since the multivariate model of the five GDP time series gives some inappropriate cycle correlations, we move to build bivariate models. Only two GDP time series are modelled at a time, namely USA and EURO-area, USA and GBR, USA and Sweden and lastly USA and Japan. We constrain the cycles' damping factor and the frequency to be equal for generating similar cycles. The results are impressive. When we build the bivariate models, we have full control over the whole modelling process. The cycle correlations of each area with USA are; the Euro-area cycle is lagging by a quarter with correlation 0.49, the GBR is no lagging with correlation 0.51, the Swedish cycle shows 8 quarters lagging with correlation 0.4, and the Japanese cycle shows 3 quarters lagging with correlation 0.46. We compare the cycle correlation of the bivariate models with the one by Benedictow and Johansen (2005). The STM shows smaller correlations than the one by Benedictow and Johansen (2005). A possible reason may be the STM's structure of decomposing a time series into different components, which is not possible to obtain with the HP-filter.

An overall performance of STM is appropriate and reasonable. However, one thing should be mentioned for further study. STM or the statistical program for STM , STAMP, is a sensitive tool. It gives fairly different results by small changes of the variables' length, interventions, and so on. This means that we should understand the theory and application of the structural model before hand, which will provide balanced controls over the modelling process.

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1. Introduction

A Structural Time Series Model (STM), is formulated directly in terms of unobserved components, such as a trend (level and slope), a seasonal, a cycle and an irregular component (disturbances). This is called ‘decomposition’, and each component can have direct economic interpretation though this process. STM is relatively new compared to other methods, however it has been suggested to be better than others in some cases;

…may have advantages over the widely used vector autoregressive (VAR) representations. For example, if the data are well represented by slowly changing trends upon which are superimposed short-term movements, the differenced observations will be almost non-invertible, leading to long lags, many parameters, and unit root and cointegration tests with poor properties… (Harvey and Koopman (1997 p270))

… in particular, information based on mechanically detrended series (such as HP-filter), can easily give a spurious impression of cyclical behavior. Analysis based on autoregressive-integrated-moving average (ARIMA) models can also be misleading if such models are chosen primarily on grounds of parsimony. We argue here that structural time- series models provide the most useful framework within which to present stylized facts on time series… (Harvey and Jaeger (1993 p231))

A Seemingly Unrelated Time Series Equation (SUTSE) model consists of several dependent and independent variables with correlated disturbances. When we analyze SUTSE, STM captures the cointegration between series, and eventually, it detects common factors of the series, i.e. common trend, seasonality and/or cycles. This is useful in multivariate modeling to analyze dynamics in each series with cointegration. An important advantage of STM is its forecasting capability. Because of the individually decomposed factors, STM can forecast each component separately. Hence, STM can forecast the actual series as well as the trend and cycles. The estimated trend and cycles have historical background, so we can rely on its consistency near future in the model. Thus the short-term future trend and cyclical movements can be explained well in STM.

Statistics Norway (SSB)’s macroeconomic model, KVARTS, uses a weighted sum of GDP in USA, EURO area, GBR, Sweden and Japan as market indicator. They are Norway's major trading partners, and their economic performances have a great effect on Norwegian economy. Although the importance of their role in Norwegian economy, their GDPs have been treated exogenously in KVARTS. It gives a practical reason to build a simultaneous model representing these five areas, and STM is thought to be a proper method to construct the model. STM is a powerful method for analyzing multivariate time series with possible cointegration. It detects common factors explicitly to show the short-run dynamics of the series and it forecasts each component separately. A GDP growth is generally driven by both international and domestic sources, and the international driving sources are somewhat similar, when we consider countries like, USA, EURO area, GBR, Sweden and Japan i.e. they share same international trading environment. Thus it is possible to find a common feature in their cycles of GDP growths. For this, we can build individual univariate STM for each area with consideration of structural shifts and outliers, and then extend the model to multivariate case.

This thesis is divided into two parts, one which studies the univariate models, and the other which studies the multivariate models. Each part starts with a short theoretical background followed by the models of the GDP time series.

The data is quarterly GDP time series in USA, EURO area, GBR, Sweden and Japan from 1960.1 to 2005.2. It is provided by originally OECD (Economic Outlook No.78) and reproduced by SSB. The data is presented in their own currencies. The logarithms of GDP time series are used in all models. Structural Time Series Analyser, Modeller and Predictor (STAMP) program is used to estimate the model. It is designed for modelling and forecasting time series using the structural time series approach, and is a powerful tool for constructing a model with stochastic or deterministic components and detecting common factors as well as test diagnostics. It also supports various graphical options. PcGive is used for the correlations between each series and their lags. Excel is used for the simple correlation graphs

2. Univariate time series model

2.1 Introduction

The modern business cycle theory is important for economic policy decisions. It is because most of economic variables like GDP are growing and fluctuating at the same time, and a correct view of the fluctuation will affect greatly on the economic policy for future periods. We refer to the growing part a trend and the fluctuating part a cycle. A trend is the model's long-term movement. In the case of GDP, a positive trend implies a potential growth of the economy. With current input of capital and labor, we can expect a certain productivity growth of the economy, and this may be a simplest example of how a trend comes into place. A cycle represents a short-term movement of the economy with some kind of regular behavior, which is repeated again and again over time.

The key concepts of a business cycle just mentioned are widely agreed among economists. However, the statistical method to identify the business cycle varies between studies. In this thesis we use the unobserved component (UC) model, also known as, the structural time series model (STM), for identifying the business cycle, Harvey (1993). This method is relatively new, but considered as an appropriate decomposition method than others, such as the HP-filter, Bjørnland (2000). A STM is built by extracting trends and cycles from unobserved components, and the parameters are estimated by maximum likelihood. Once this estimation process has been done, optimal estimates of the components are obtained by smoothing algorithms.

Harvey (2002) gives a rather compact version of the modeling process of STM, he says that,

"*The statistical treatment of unobserved component models is based on the state space form (SSF). Once a model has been put in SSF, the Kalman filter yields estimators of the components based on current and past observations. Signal extraction is based on all the information in the sample. Signal extraction is based on smoothing recursions, which run backwards from the last observation. Predictions made by extending the Kalman filter forward root mean square errors (RMSEs) can be computed for all estimators and prediction intervals constructed." (Harvey (2002), p2)*

It is not a simple task to completely understand the technical background of the process, thus we will concentrate on the application and interpretation of the model. We begin this section from looking at the decomposing options in STM. After that, we build univariate models for the GDP series of USA, EURO-area, GBR, Sweden and Japan. We use the program STAMP (Structural Time Series Analyser, Modeller and Predictor) for this thesis. The application and usefulness of the program will be examined through the thesis.

2.1.1 Decomposition

In STM, the dependent variable is decomposed into a trend, seasonal, cycle and irregular component. As mentioned above, a trend is the long-term growth of the model, and it can be divided into two factors, level and slope. A level is an actual value of the trend and a slope is a tendency to grow of the trend. A slope is not always necessary in a model, because some data series move around their level randomly without any tendency to grow. A slope component is used when we have data with continuous growth, such as GDP, income, population, etc. A seasonal component may be necessary when we have quarterly or monthly or daily time series. A seasonal pattern of a time series will be captured and presented as an individual component. Like the other components, a direct interpretation of the seasonal component is possible. In this thesis, we are not interested in the seasonal movement as such, so we use seasonally adjusted time series. This means that it won't be any seasonal effects in our model. A cycle component represents the model's short-term movement. When we have defined a trend of a seasonally adjusted time series, there will be two components left, namely cyclical and irregular components. A stochastic cycle is constructed by shocking the prior set deterministic cycle with disturbances and an application of a damping factor. This process captures the model's cyclical movement, which generally lasts 4 to 8 years. An irregular component is white noises, indicating the unexplained movement of the model.

2.1.1.1 A trend plus noise model

A local linear trend allows both level and slope to be stochastic. The level and the slope are estimated by giving more weight on the most recent observations.

The local linear trend model for a set of observations, y_t, $t = 1, 2, \ldots, T$ consists of a stochastic trend and an irregular component,

$$y_t = \mu_t + \varepsilon_t,\ t = 1, \ldots, T,\ \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2),$$

the trend, μ_t is composed of a stochastic level component and a slope component,

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t,\ \eta_t \sim NID\ (0, \sigma_\eta^2)$$
$$\beta_t = \beta_{t-1} + \zeta_t, \qquad \zeta_t \sim NID\ (0, \sigma_\zeta^2)\ , \qquad \text{(Local linear trend)}$$

where the irregular, level and slope disturbances, ε_t, η_t and ζ_t respectively, are mutually independent and uncorrelated with each other. Each disturbance is normally distributed with zero mean and variance σ_ε^2, σ_η^2 and σ_ζ^2, respectively. The effect of η_t is to allow the level of the trend to shift up and down, while, ζ_t allows the slope to change. When σ_ζ^2 is zero ($\beta_t = \beta_{t-1} = \beta$) with non-zero σ_η^2, the model will have a fixed slope, which is a random walk with a constant drift β.

$$\mu_t = \mu_{t-1} + \beta + \eta_t,\ \eta_t \sim NID\ (0, \sigma_\eta^2)$$

If both σ_η^2 and σ_ζ^2 are zero, the model will have a deterministic trend.

A smooth trend is constructed by a fixed level ($\sigma_\eta^2 = 0$) and a stochastic slope (σ_ζ^2 is positive), and that is,

$$\mu_t = \mu_{t-1} + \beta_{t-1}$$
$$\beta_t = \beta_{t-1} + \zeta_t, \qquad \zeta_t \sim NID\ (0, \sigma_\zeta^2), \qquad \text{(smooth trend)}$$

this is also called an integrated random walk (IRW) trend. This trend tends to be relatively smooth. The smooth trend model is often used for GDP analysis and in that case, it is usually combined with cyclical components.

2.1.1.2 A cycle plus noise model

A stochastic trend model of a seasonally adjusted economic time series doesn't capture the short-term movement of the series by itself. Including a serially correlated stationary component, ψ_t, the short-term movement may be captured, and this is the model's cycle. The modeling process for a stochastic cycle is,

$$\begin{pmatrix} \psi_t \\ \psi^*_t \end{pmatrix} = \rho \begin{pmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{pmatrix} \begin{pmatrix} \psi_{t-1} \\ \psi^*_{t-1} \end{pmatrix} + \begin{pmatrix} k_t \\ k^*_t \end{pmatrix}, \quad t = 1,\ldots,T,$$

the cycle can be written again,

$$\psi_t = \rho\cos\lambda_c\,\psi_{t-1} + \rho\sin\lambda_c\,\psi^*_{t-1} + k_t$$
$$\psi^*_t = -\rho\sin\lambda_c\,\psi_{t-1} + \rho\cos\lambda_c\,\psi^*_{t-1} + k^*_t,$$

where the λ_c is frequency, ρ is a damping factor with condition $0 < \lambda_c < \pi$, $0 < \rho < 1$. k_t and k^*_t are white noises with zero mean and covariance σ_k^2. If λ_c is zero or π, the cyclical process will be reduced to AR (1) ($\psi_t = \rho\psi_{t-1} + k_t$, if λ_c is zero or π). The damping factor should be strictly less than unity for stationary process. When the damping factor equals to one, there will be no restrictions for the cyclical movement, resulting in extending the amplitude of the cycle.

2.1.1.3 A trend-cycle model

The model we are eventually interested in is a trend-cycle model. Bear in mind that our seasonally adjusted data is growing and fluctuating at the same time. Applying the trend-cycle model can capture both short-term and long-term movements of the series, and how the model is, will depend on our choice of restrictions based on theoretical and empirical knowledge.

A basic trend-cycle model is,

$$y_t = \mu_t + \psi_t + \varepsilon_t,\ t = 1, \ldots, T,\ \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2)$$

Where the trend and the cycles are,

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t,\ \eta_t \sim NID\ (0, \sigma_\eta^2)$$

$$\beta_t = \beta_{t-1} + \zeta_t, \qquad \zeta_t \sim NID\ (0, \sigma_\zeta^2)$$

$$\psi_t = \rho \cos \lambda_c\ \psi_{t-1} + \rho\ \sin \lambda_c\ \psi^*_{t-1} + k_t$$

$$\psi^*_t = -\rho \sin \lambda_c\ \psi_{t-1} + \rho\ \cos \lambda_c\ \psi^*_{t-1} + k^*_t$$

A deterministic trend means that the time series data grow in fixed rate and it is hardly possible to find such trend in complicated modern macroeconomic variables. However, there should be a careful consideration to apply a stochastic trend too. Allowing both level and slope to be stochastic means that we let the trend explain most of the model's variation, leaving very little room for the cyclical movement. In other words, the model's stochastic trend will fit the actual data well, however with this high degree of flexibility, it will be difficult to forecast the future movement. Thus when we build a STM, we should consider whether we put more weight on modeling the actual data series, or forecasting the future movement. Then we decide how flexible an useful model ought to be.

Harvey *et al*. (2000) say that the use of a smooth trend with a cycle often leads to a more attractive decomposition. This would make sense since the smooth trend will allow the cycle to explain most of model's variation. This will be especially useful for forecasting. With a smooth trend model, the trend will be less stochastic, and we know that the trend won't be affected by small shocks in near future. Once the smooth trend being estimated, the rest of model's variation will be explained by the cycle, and this will be continued in near future. In this way, forecasting of the short-term movement can be carried out. This is why it is attractive to use a smooth trend for GDP time series.

We can also detect the smooth trend by observing the level variance being zero. This can be done by observing the model’s output after estimation with STAMP.

2.1.2 Interventions

The STAMP program can detect unusual movements by means of residuals' normality test. The function 'Auxiliary residuals' is designed to detect unusual movements in the fitted time series model. These residuals are the smoothed estimates of the disturbances associated with the irregular, level and slope component. These components are tested separately, and STAMP reports an outlier for the unusual irregular component, and a structural break will be reported for the unusual level component.

An outlier is an abnormally large disturbance value in irregular component. It represents a special event, which happened at a particular time, and the effect will die out later on. It is interpreted as an instant shock, and when we apply it with STAMP, we use a dummy variable, which have a value one in that particular time. In the case of GDP time series, a nationwide strike may be an example of an outlier.

A structural break is in which the level of the series shifts up and down by a special event, and it is interpreted as a structural shift in the time series. A dummy variable for a structural break takes value one for all the period after the event. This represents a permanent shock in the economy. A change of the government's tax regime may be an example of a structural break.

It seems to be simple when it comes to an interpretation of these interventions, since it is defined clearly as above. However, through this thesis, it has been realized that it needs consideration and flexibility to use interventions. STAMP is a tool to detect some unusual movements in time series, but it doesn't give any further information. This implies that we have to find the historical background for the interventions. In this process, it is realized that GDP time series is somewhat different from other variables, such as the amount of rainfall in the Nail River or the fatality rate in UK before and after the introduction of seat belt law in 1983. Harvey et al. (2000) use these variables as examples for intervention and they show

how effective to apply the intervention in such models. The problem we have with GDP time series starts from the nature of a GDP time series itself. It is an aggregate of all national income or expenditure of the whole economy, and it is not simple to conclude that GDP reacts instantly to an event as other simple variables. For example, we know already that the first and second oil shocks in 1970's gave great negative influences on many countries' economy, however, it is hard to pinpoint exact time (or in this case, which quarter) when the economy reacted to the oil shocks as a whole. Thus when STAMP reports outliers or structural breaks of a GDP time series, we have to be flexible to admit that sometimes it is difficult to find certain incidents, which cause the unusual movements in that particular time. However, the existence of an intervention is worth to study, since, as we will see later in the univariate models for each GDP time series, the interventions affect greatly on modeling process, making trend more stochastic or not. This influences further on the cycle's length or amplitude. Eventually the forecast will be different by the use of interventions. What is most appropriate will depend on the variable under consideration.

2.1.3 Forecasting with the STM model

There are two important points to consider in modeling GDP time series, the first is how well the model explains (or fits) the actual data of the economy, and the other is how good the model forecasts the economy after a year or two or three. These are, in a sense, two separable questions, but we have to remember to keep the balance between these two points when we build a model.

In a STM, all components are forecasted individually, and direct interpretations of each component are also possible in forecast. Since, we are interested in the short-term movement in near future, we focus on the cyclical development in forecast. To examine the cyclical movement, we have to choose the flexibility of the trend in modeling process in advance. If we choose a local linear trend (a stochastic level plus a stochastic slope) for the GDP time series, the model fits best to the actual data. However, it will give very poor forecast, because the short-term movements are absorbed into the stochastic trend instead of the cycle. Because of this reason, the smooth trend (a fixed level plus a stochastic slope) is used in this thesis, and it gives appropriate forecast of the cyclical component. As we will see later in the USA, GBR, Swedish and Japanese model, the application of interventions leads the model to forecast differently from the model without interventions. Thus an alternative model will be presented after discussion of the main model for each GDP time series.

To examine the reliability of each model's forecast, the forecasted annual growth rates from 2005.3 to 2007.4 are presented later, and we will compare them with the growth rate projections from the OECD report (2005, Economic Outlook No. 78). Regarding the forecast, a question has occurred through this thesis. Should we forecast the GDP time series itself, or are we better served by do we have to forecasting each component separately? From STAMP, we can get each component's forecast. Forecasts for trend and cycle are estimated separately and it is possible to interpret each component's forecast at once. However, it is shown later in this thesis, this way of forecasting may lead to poor forecasts. When STAMP generates a model, it places more weight on the latest values. As a result, the trend tends to be following latest development of the series, meaning that if the series has been growing rapidly during the last two or three quarters, the trend will show continuous rapid growth. In this case, the cycle will be in recession even though the economy is actually in high growth periods. By observing only the forecast of the cycle, someone may incorrectly conclude that the economy will experience a recession in near future. This is caused by using a stochastic trend. To avoid this problem, we may use the forecasted growth rate of the GDP time series (not the individual components). A forecasted growth rate includes both trend and cycle and is giving overall forecast of the GDP time series. The forecasted growth rates will be presented for each univariate models.

2.1.4 The variances of the model

A model with a smooth trend, cycle and disturbance is,

$y_t = \mu_t + \psi_t + \varepsilon_t$, $t = 1, \ldots, T$, $\varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2)$

As an example, we report the results of a trend-cycle model for the seasonally adjusted USA GDP data. The results are presented in table 1.

Table 1. Variances of component, USA GDP Structural Time series Model

Variance of disturbance (q-ratio)	Level, σ_η^2	0(0,0000)
	Slope, σ_ζ^2	0,00000184(0,0554)
	Cycle, σ_ψ^2	0,0000333(1,0000)
	Iirregular, σ_ε^2	0(0,0000)
Cycle	Variance, σ_k^2	0,000206
	Average length *(year)*	5,002
	Frequency, λ	0,314
	Damping factor, ρ	0,916

The sum of all the component's variances amounts to the estimated value of σ_y^2. From the table we thus obtain that σ_y^2 equals to 0.00003534. Since these components are assumed to be uncorrelated with each other, we disregard the covariance between each component. One of the basic points is to check the unexplained disturbance's variance, σ_ε^2, to be as small as possible, and let the other components, such as the trend and the cycle explain most of the model's variation. In our smooth trend model, the larger values for σ_ξ^2 and σ_k^2 mean the greater the stochastic movements in the trend and the cycle. In this thesis, it is not simple to know whether the trend or the cycle will explain most of the model's variation. It is the matter of how flexible the trend would be, and examining the data in addition to prior economic knowledge can be applied in this process. As it has been used in many literatures for GDP series (it is most of articles by Harvey, Koopman and many others who studies UC) a smooth trend (a fixed level with a stochastic slope) has been a starting point in this thesis. This means that we set a relatively smooth trend and let the cycle explain the most part of the model's variation. One of the most popular detrending methods, HP-filter is actually one of the special cases of the smooth trend model with the signal-noise ratio, $q = \sigma_\xi^2 / \sigma_\varepsilon^2$, is set to 1/1600 for quarterly data, Harvey (2002). However, we examine other modeling methods such as a local linear trend (a stochastic level with a stochastic slope) plus cycle model, and a deterministic trend (a fixed level with a fixed slope) plus cycle model, and see the properties and usefulness of such models. Examining the q-ratio will give us useful information for the process. The q-ratios are the ratios of each variance to the largest, and by observing the q-ratio, we can examine which of the components is the most volatile (in relative terms).

It should be noted that the cycle's disturbance variance, σ_k^2, is different from the variance of cycle itself, σ_ψ^2. σ_k^2 is responsible for making the cycle be stochastic, in other words, the greater the value for σ_k^2, the more stochastic the cycle is. The relationship between these two variances is, Harvey (1989),

$$\sigma_k^2 = (1-\rho^2)\,\sigma_\psi^2$$

When the damping factor converges to unity, the cycle's disturbance, σ_k^2, will converge to zero, which implies a deterministic trend.

2.2 Univariate GDP structural time series models - USA, EURO-area, GBR, Sweden and Japan

Following the theoretical information in previous section, we build univariate structural time series models for these five areas. We use the quarterly time series of real GDP from The Economic Outlook No. 78 (OECD), and the logarithm of the time series is used for estimation. As explained above, we also remove the seasonal effects in each series prior to estimation.

2.2.1 Univariate GDP time series model, USA

2.2.1.1 Data

We model the seasonally adjusted quarterly USA GDP time series from 1960.1 until 2005.3. It is the market volume in US dollar (USD), and is chained at 2000.

2.2.1.2 Modeling USA GDP time series

The estimated model with a smooth trend, a cycle and interventions is,

L.GDP.USA = Trend + Cycle + Outlier1970.4 + Level-shift1978.2 + Irregular

Two interventions are detected by STAMP, one in 1970.4 as an outlier and the other in 1978.2 as a level shift. The estimated parameters for the regression are shown in table 2, with coefficients of each variable, variances of disturbance, goodness of fit (Rd^2) and prediction test (Prediction Failure Chi^2).

Table 2. Estimated parameters for the USA GDP structural time series model

Coefficient	Level	16,223**
	Slope	0,00808*
	Cycle_1	0.00754
	Cycle_2	(-) 0.00068
	Irr1970.4	(-) 0.018**
	Lev1978.2	0,032**
Variance of disturbance (q-ratio)	Level, σ_η^2	0
	Slope, σ_ζ^2	0,00000184(0,0554)
	Cycle, σ_ψ^2	0,0000333(1,0000)
	Iirregular, σ_ε^2	0
Cycle	Variance, σ_k^2	0,000206
	Average length *(year)*	5,002
	Frequency, λ	0,314
	Damping factor, ρ	0,916
Rd^2		0,213
Prediction Failure Chi^2 (20)		5,99(p-value: 0.99)

* Statistically significant with 5% significance level, ** statistically significant with 1% significance level

In the table, several points are worth noting. The two interventions are statistically significant with 1% significant level, and the cycle explains most of the models variation, which is implied by the q-ratio being equal to one. The variance of the irregular component disturbance is zero, which tells us that all the variation in the USA GDP time series is explained by the trend, cycle and interventions. This means that there is no unexplained movement in the model. The cycle's average length is about 5 years. We can test if the model forecasts well by the prediction function. STAMP predicts the last 20 quarters (from 2000.4 to 2005.3) with using the data until 2000.3. The *Prediction Failure Chi²* tests whether the prediction coincides with the actual data for the post periods, the null-hypothesis. The result tells us that we cannot reject the null-hypothesis, meaning that the model predicts well for the post periods. The graphs of each component give us more intuitive information about the model.

Figure 1 shows graphs for each component. We see the slope component varies a lot, which makes the trend becomes more stochastic. From the graph of the cycle component, we see that USA had a big boom during 1972-1973, followed by a deep downturn in 1974-1975. We also notice that a great downturn in 1982-1983. It is interesting to compare the result with the report from National Bureau of Economic Research (NBER), which represents the US business cycle expansions and counteractions. It is shown in figure 2.

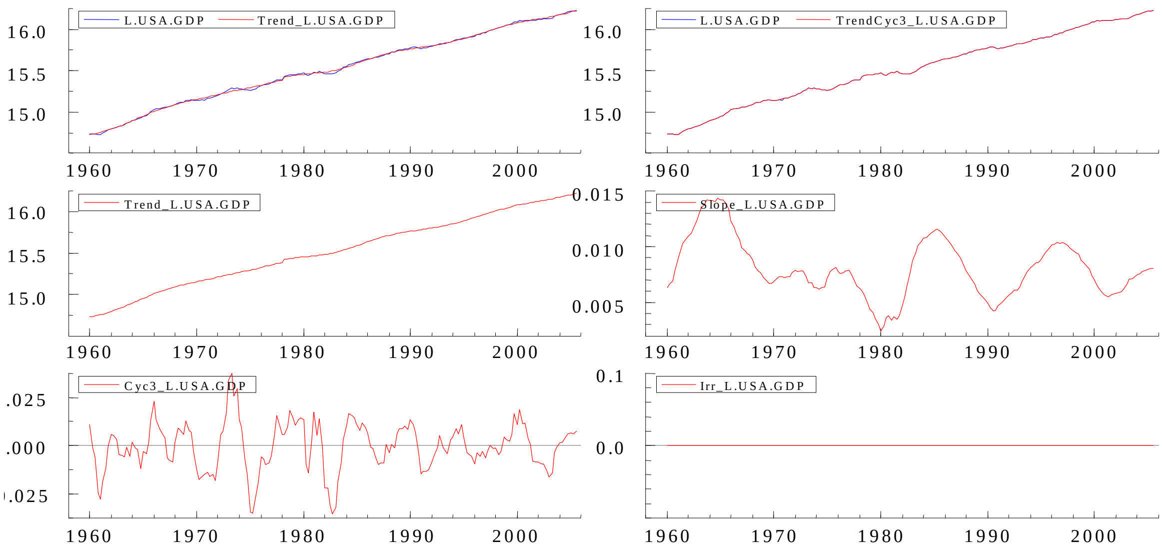

Figure 1. Components of the USA GDP structural time series

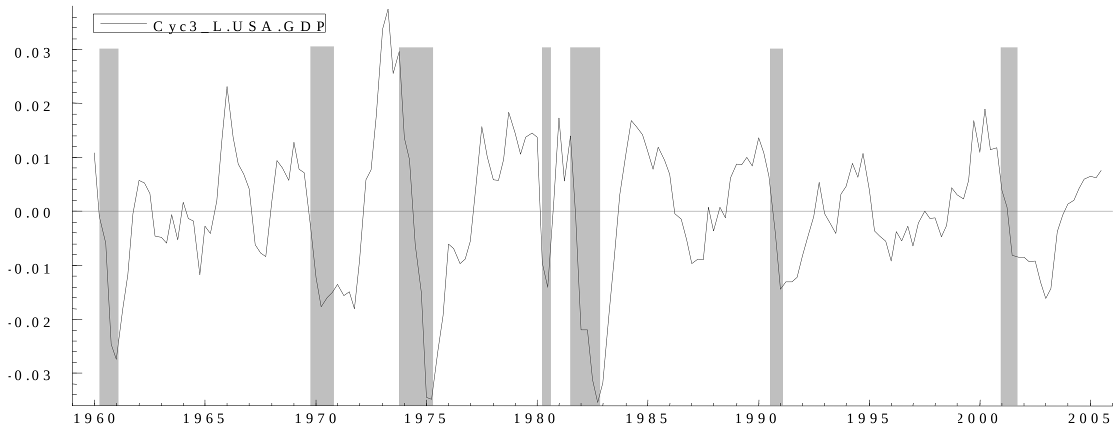

Figure 2. The cycle. The shaded area: from peaks to troughs, NBER report for USA GDP

NBER identifies 37 peaks and 38 troughs in US economy between 1850 and 2005 (NBER, 2005). There are 7 peaks and 7 troughs during the sample period from 1960 to 2005. The peaks are 1960.2, 1969.4, 1973.4, 1980.1, 1981.3, 1990.3 and 2001.1. The troughs are 1961.1, 1970.4, 1975.1, 1980.3, 1982.4, 1991.1 and 2001.4. From the figure 2, we see that the model's troughs match to the NBER's troughs identically (except the last trough in 2001.4), while the model's peaks are reported earlier (around one year) than the peaks from NBER. It seems to take longer time from a peak to a trough in the STM than what NBER reports, but it needs more study to obtain clearer knowledge about the differences. Some cycles from the model are not reported by NBER, however, it is quite interesting to notice that the model catches the peaks and troughs as NBER does, because NBER use a lot of macroeconomic and specialized information to examine all economic aspects to identify peaks and troughs, while our model is a pure statistical decomposition of the USA GDP time series.

Figure 3 shows the forecast of the cyclical component of the USA GDP structural time series.

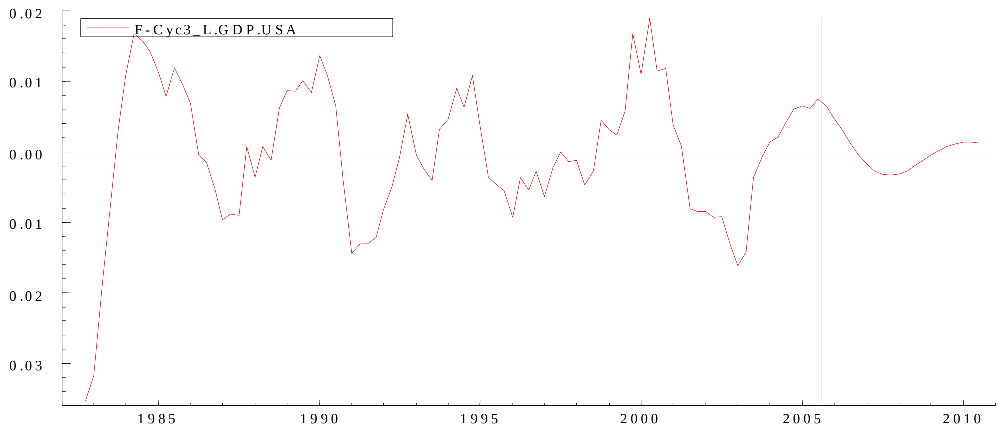

Figure 3. Forecast for the cyclical component of the USA GDP structural time series

The forecast graph indicates that the US economy is turned to a recession period after the peak in 2005.3, and it is forecasted to last until 2007.2.

The automatically selected interventions need consideration when we include them into the model. STAMP detects unusual movements in the GDP time series by testing the normality of the residuals of each component. As mentioned earlier, it is difficult to identify the background of the interventions in GDP time series. We should be extra careful to use a level shift, since a level shift is regarded as a permanent shock. A permanent shock means that all the following periods will be influenced by the level shift. For the USA GDP time series, two interventions are detected, an outlier in 1970.4 and a level shift in 1978.2. In the US economic history, there are not single events in 1970.4 and 1978.2, which can support the use of these interventions. Even though we have realized that an intervention in a GDP time series captures an aggregate outcome of the whole economy, it is not so convincing to use the interventions when we can not find a historical reason for it. Thus we build an alternative model without the interventions, and see the differences between models with and without the interventions.

2.2.1.3 An alternative Model for the USA GDP time series, without the interventions

Table 3 shows the variances of disturbances and cycle component of the alternative model. To compare the results, we put the result from model 1 (model with the interventions) besides.

Table 3. Estimated parameters for the USA GDP structural time series model with and without interventions

		Model1 (with interventions)	Model2 (without interventions)
Variance of disturbance (q-ratio)	Level, σ_η^2	0	0
	Slope, σ_ζ^2	0,00000184(0,0554)	0,00000009067(0,0018)
	Cycle, σ_ψ^2	0,0000333(1,0000)	0,00005024(1,0000)
	Irregular, σ_ε^2	0	0
Cycle	Variance, σ_κ^2	0,000206	0.0005378
	Average length *(year)*	5,002	8,091
	Frequency, λ	0,314	0.194
	Damping factor, ρ	0,916	0.952

We notice that the disturbance variance of the slope is reduced from 0,00000184 (q-ratio: 0,0554) to 0,00000009067 (q-ratio :0, 0018), while the cycle shows the other way. This implies a less stochastic slope, eventually a less stochastic trend. The cycle will explain almost all of the model's variation with the alternative model, resulting in a longer length with 8,091years.

Figure 4 shows the component graphs of the alternative model. It is clear from the graphs that the trend is close to a deterministic trend and the cycle explains most of the model's variation.

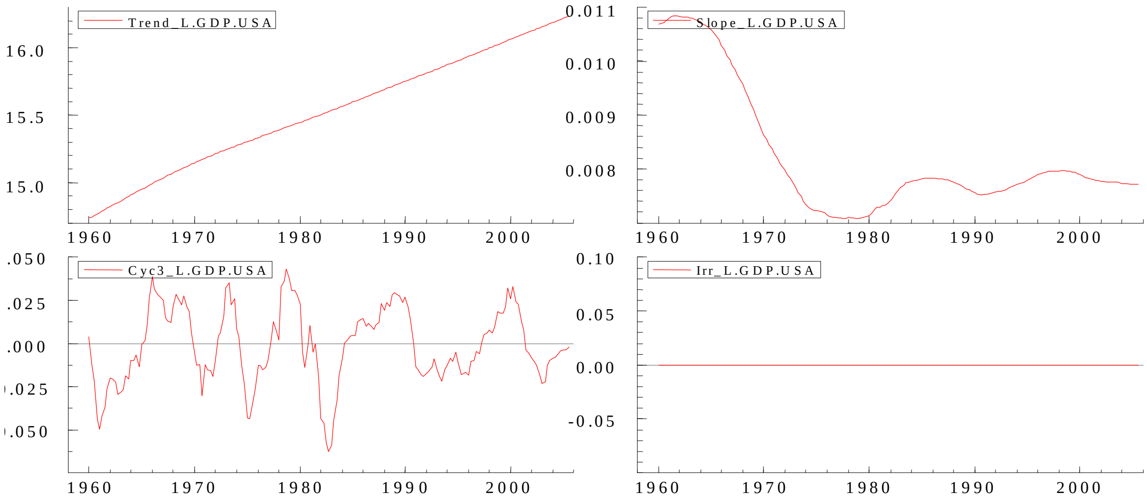

Figure 4. Components of the USA GDP structural time series model, without interventions

Figure 5 represents these two cycles. A cycle generated by the HP-filter for the USA GDP time series is also presented in the figure 5. The two models' disturbance variances of irregular components are zero. This means that there is no unexplained movement in the model. The biggest shortcoming of a HP-filter is that it can give spurious information caused by the unexplained movement, Cogley (1990). Because there is no unexplained movement in the USA case, the use of HP-filter will be reasonable, and we can observe it from the graph that these three cycles show similar movements in their behavior.

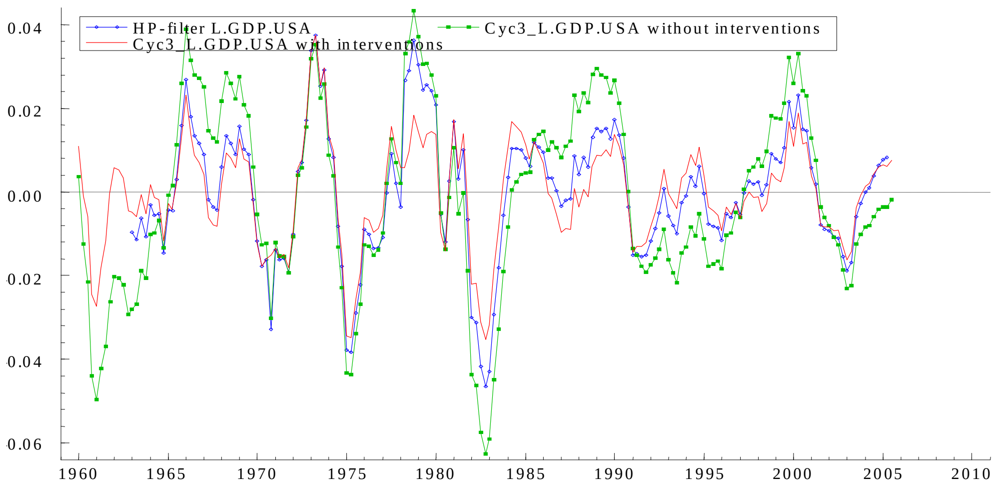

Figure 5. Cycles from the STM and HP-filtered cycle for the USA GDP time series

2.2.1.4 A comparison of the model, with and without interventions

The interventions irr1970.4 and lev1978.2, especially lev1978.2, result in a more stochastic trend by means of changes in slope variance. As we follow STAMP, the application of interventions is somewhat clear to use, however we do have a problem to identify the background for the level shift in 1978.2 as well as the outlier in 1970.4. Two choices we can consider, should we use the interventions, which STAMP reports, or should we ignore them, since we cannot find the clear historical background for the interventions? We can express this question in other way, do we accept the trend to move more freely, or do we see the trend to be more rigid, so it is close to a deterministic trend?

The first choice, which implies to use the interventions, leads us to a shorter cycle, and a more stochastic trend. This model tells us that USA economy had its peak at the second quarter in 2005, and from the third quarter in 2005, it forecasts a recession until the second quarter in 2007, where the cycle is predicted to hit the bottom.

The second choice, which implies the model without interventions, shows a longer cycle and a less stochastic trend. The trend is rigid, which almost looks like a deterministic trend. In this model, there is very little variation for the slope component, even though we build the model with a smooth trend (a fixed level plus a stochastic slope). The cycle explains most of the models variation, and this will result a longer cycle and greater amplitude. This decomposition tells us that USA economy is still expanding, and the peak is forecasted to be in the middle of 2007.

Figure 6 represents the forecasts of the cycle. The graph indicates that the level shift is the main reason for the differences in the forecasting.

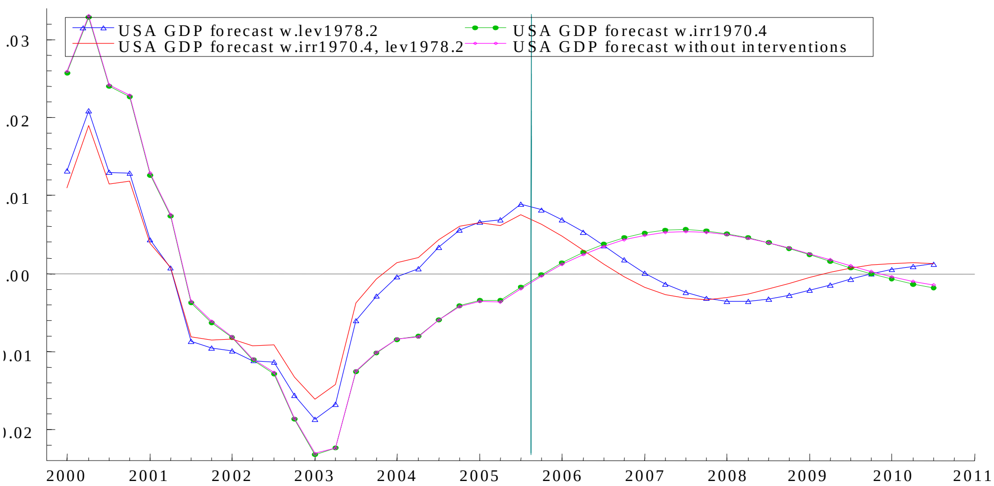

Figure 6. Forecasts with and without interventions for the USA GDP structural time series

We conclude that, at least in this case, the STM is quite sensitive to the data. As we have seen before, we obtain different models by including an intervention. After examination of the USA case, it is clear that we must take into a consideration the role played by the cycle component for the forecast. When we use STAMP to forecast the cyclical movement, the trend is also forecasted. This means that the trend itself can be forecasted for the near future, resulting in a stochastic trend in forecasting. Look at the figure 6 again, for simplicity, we compare the plain cycle (with both interventions) with the cycle with circles (no interventions). The hidden information is that the trend with interventions is more stochastic than one without interventions. Thus if we observe only the cyclical forecast, we might miss the information from the trend forecast. We suggest using the forecasted growth rate for future reference in the STM, which will include information from both trend and cycle. Table 4 shows the forecasted annual growth rates of model 1, model 2 and the forecasted growth rates to the projection report from OECD.

Table 4. Forecasted Real GDP growth rates, USA. Source: SSB and OECD

Real GDP growth forecasting (annualized, %)											
		2005		2006				2007			
		Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
USA	Model1 (with interventions)	3,8	2,8	2,6	2,5	2,5	2,6	2,7	2,9	3	3,2
	Model2 (without interventions)	3,8	3,7	3,7	3,6	3,5	3,4	3,3	3,2	3,1	3
	OECD		3,7	3,3	3,5	3,5	3,3	3,2	3,2		

We see that model 2 gives similar results as in the OECD report. This implies that both model 2 and the OECD model forecast higher long-term growth for the USA economy in the future. Even though the model 2 gives similar result as the OECD model, it is difficult to conclude that the model 2 is better model than model 1. According to the model 2, the USA economy is just turned to expansion (figure 6). But it is widely agreed that the USA economy has been in boom for several quarters at the moment. Once again, the question is how we define the trend and cycle and their stochastic aspects.

2.2.2 Univariate GDP structural time series model, EURO-area

2.2.2.1 Data

The data is aggregate GDP in market volume (in EURO, based 2001) in 12-EURO countries. The 12-EURO countries are Western-Germany, France, Italy, Austria, Belgium, Finland, Ireland, Luxembourg, Netherlands, Portugal, Spain, and Greece for the periods from 1963.1 to 1990.4. From 1991.1 to 2005.3, the data includes the German GDP as a whole instead of

Western-Germany in addition to the other 11 countries. It is the market volume in EURO (euro), and chained at 2001 as the base year.

2.2.2.2 Modeling EURO-area GDP structural time series

Figure 7 shows the EURO-area GDP. It shows possible breaks in 1974 and 1991. It is assumed to have a stochastic trend with interventions around these breaks. We build a model with a smooth trend plus a cycle.

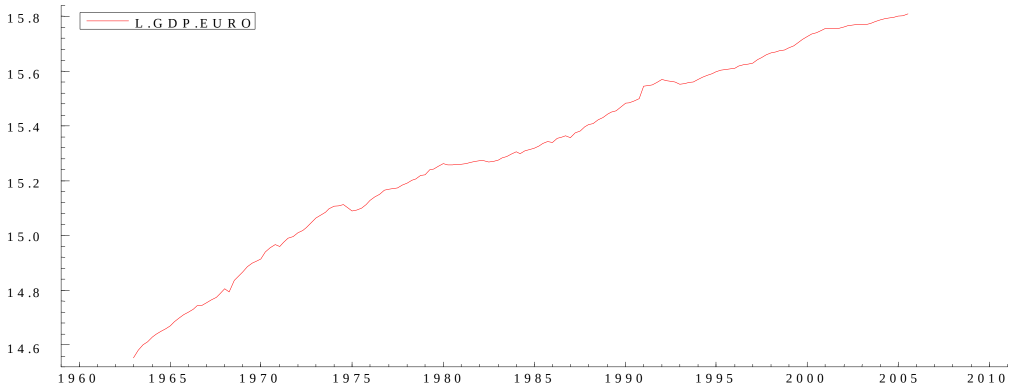

Figure 7. EURO-area GDP time series

The estimated model with a smooth trend, a cycle and interventions is,

L.GDP.EURO = Trend + Cycle + Outlier1968.2 + Level-shift1991.1 + Irregular

STAMP detects two interventions, one in 1968.2 as outlier and the other in 1991.1 as level shift. It is interesting that the program doesn't report a level shift in 1974, even though it looks like one. The estimated parameters for the regression are shown in table 5, with coefficients of each variable, variances of disturbance, goodness of fit (Rd^2) and prediction test (Prediction Failure Chi^2).

Table 5. Estimated parameters for the EURO-area GDP structural time series model

Coefficient	Level	15.808**
	Slope	0.0036092
	Cycle_1	0.0016380
	Cycle_2	0.0015268
	Irr1968.2	(-)0.027054**
	Lev1991.1	0.040221**
Variance of disturbance (q-ratio)	Level, σ_η^2	0
	Slope, σ_ζ^2	0,00000131(0.0787)
	Cycle, σ_ψ^2	0,00001665(1,0000)
	Iirregular, σ_ε^2	0

Cycle	Variance, σ_κ^2 Average length *(year)* Frequency, λ Damping factor, ρ	0,0000676 4.618 0.340098 0.868169
Rd²		0.477
Prediction Failure Chi² (20)		4.11(p-value: 0.9999)

* Statistically significant with 5% significance level, ** statistically significant with 1% significance level

Figure 8 shows the graphs of each component.

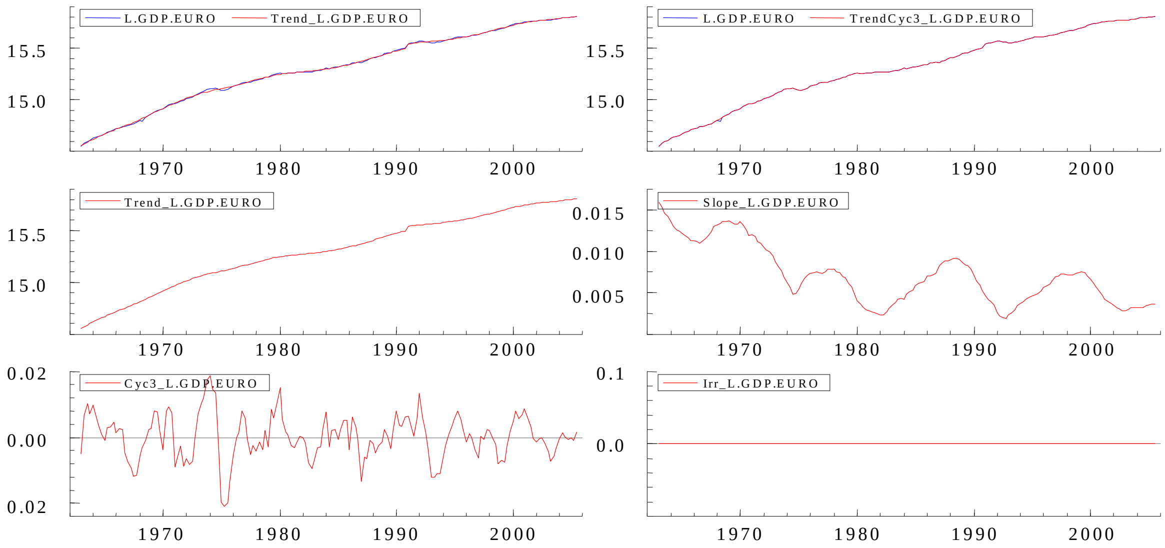

Figure 8. Components of the EURO-area GDP structural time series model

The model describes the EURO GDP series well, with high Rd², 0.477. The two interventions are statistically significant with 1% significant level. It is fairly understandable, since EURO-area has been experienced several noticeable events in the history, and their influences on the economic development can be the background of the interventions. The outlier in 1968.2 may have caused by the big anti-government movement, which started in USA and spread to European countries, mainly France. This incident caused a severe economic slowdown in most of European countries, and STAMP reports a negative coefficient for this period. The level shift in 1991.1 represents the German reunification. This might be a rather quantitative than qualitative change, because the data represents EURO-countries with only Western Germany until 1990.4 and then twelve EURO-countries including the whole Germany from 1991.1. It was assumed to have a break in 1974, but this is explained by the cycle, which shows a rapid downturn in 1974 in the cycle. This means that the model reports the first oil-shock as a cyclical movement, not a shock that has a permanent effect on the economy. The movement in slope component makes the trend be more stochastic, which results in the shorter cycle and smaller amplitude. The result for the *Prediction Failure Chi²* test tells us that we cannot reject the null-hypothesis (the predicted value is same as the actual value), meaning that the model predicts well for the post periods. Figure 9 represents the model's prediction.

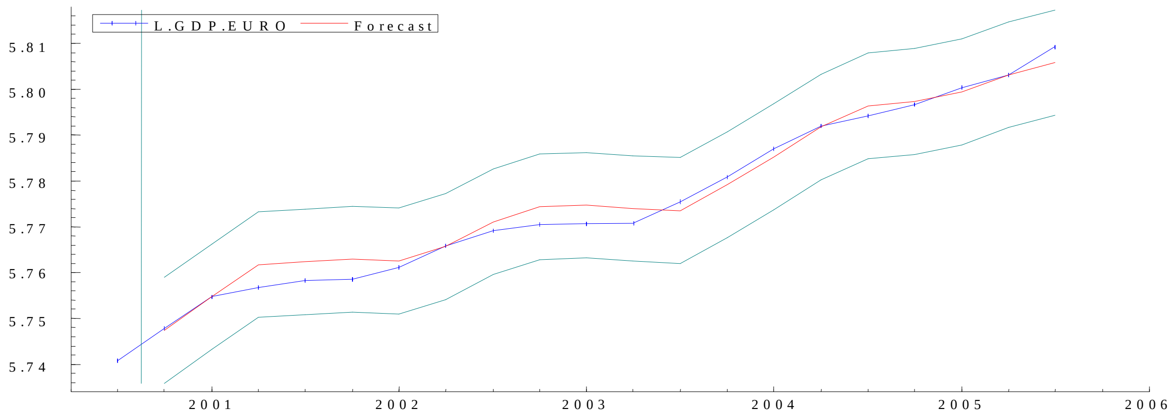

Figure 9. Post-period prediction of the EURO-area GDP structural time series, 2000.3 - 2005.3

It is interesting to compare the cycle with the HP-filter. Figure 10 shows two cycles, one generated by the STM and the other by HP-filter. We can notice that these are similar in their behavior except the intervention periods (1968.2 and 1991.1). Like USA GDP series, the HP-filter matches well with the model's cyclical component, since the irregular component in our model (see the graph of the irregular component above) has zero variation. This points out that the other components (mainly the cycle) explain the model's variation.

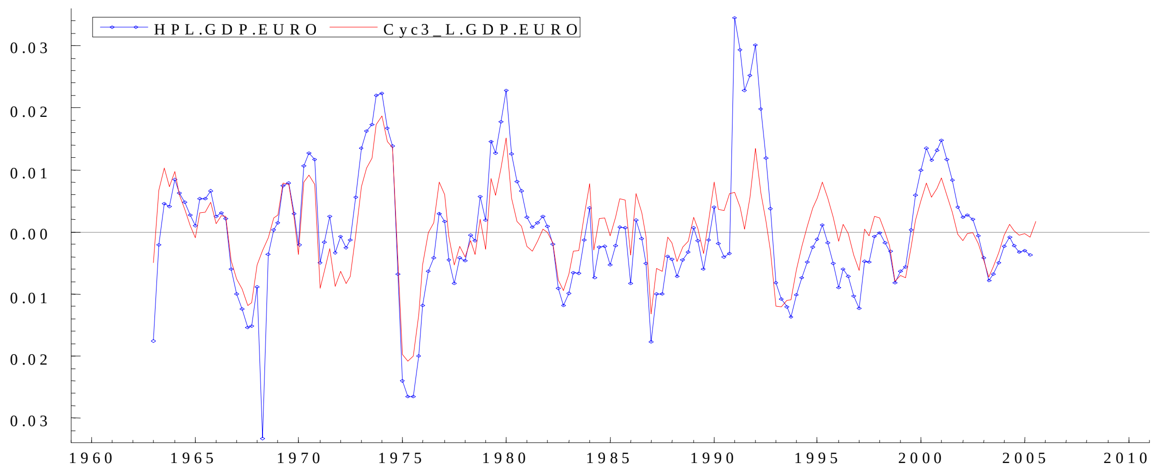

Figure 10. Cycle and HP-filtered cycle. EURO-area GDP time series

When it comes to forecasts, the model reports that the EURO-area's economy is on the peak at the moment, and it will be experiencing recession periods until the first quarter of 2008.
The graph with the forecasts is shown in figure 11.

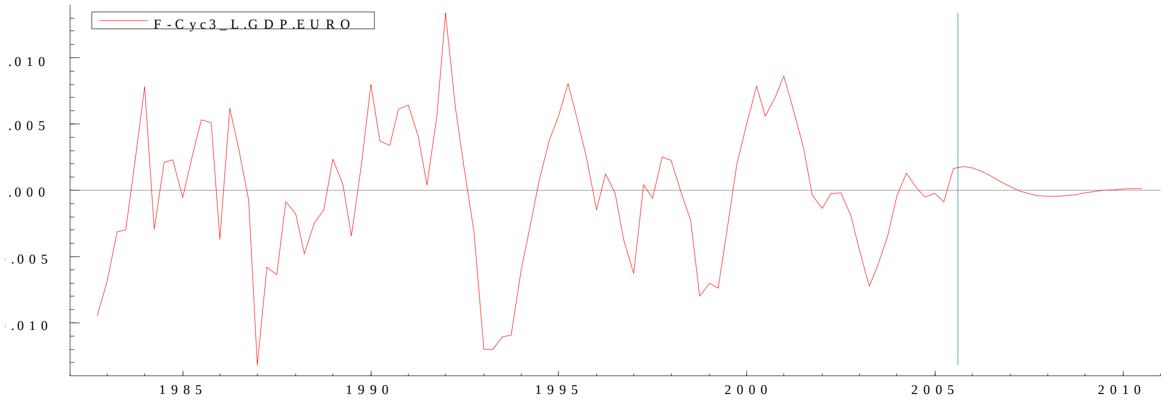

Figure 11. Forecast for the cycle component, EURO-area GDP structural time series

2.2.2.3 A note on the impact of the German reunification

The data set is actually divided into two different groups, one with Western Germany (until 1990.4) and the other with the united Germany (from 1991.1). The application of a level shift in 1991.1 makes the model adapt the change, and it results in an appropriate model that we analyzed above. But what if we build a model with only the data from 1991.1 which entails that we only use the EURO-area data for the period with the united Germany. This idea occurred because the data from 1963.1 to 2005.3 forecasts quite different growth rates from the OECD forecasting report (look at the table 6 below).

Table 6. Real GDP growth rates, EURO-area. Source: SSB and OECD

Real GDP growth forecasting (annualized, %)											
		2005		2006				2007			
		Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
EURO-area	Model1 (data from 1963.1)	2.4	1.5	1.4	1.3	1.3	1.3	1.3	1.3	1.4	1.4
	Model2 (data from 1991.1)	2.4	2.0	2.0	2.0	2.0	1.9	1.8	1.8	1.8	1.8
	OECD		2.2	1.9	2.0	2.2	2.1	2.2	2.2		

The model with the data from 1991.1 seems to generate a too short cycle, with length about 2.91years. This may imply that the time series is too short to build a STM. However, the model reports reasonable values for forecasting, which are similar to the OECD forecasting. It doesn't prove that this model is better than the other. The point is to show how sensitive the

STAMP is. A small change in the data set can forecast quite differently. We have to bear in mind that in addition to master the program, there need economic knowledge, full information of the data and flexibility, when we build a model with STAMP.

2.2.3 Univariate GDP structural time series model, GBR

2.2.3.1 Data

We model the seasonally adjusted quarterly GBR GDP time series from 1960.1 until 2005.2. It is the market volume in Pound Sterling (GBP), and chained at 2002 as the base year.

2.2.3.2 Modeling GBR GDP time series

Figure 12 shows the GBR GDP. It shows possible breaks around 1963, 1979 and 1991. Two possible outliers are in 1973 and 1979. It is assumed to have a stochastic trend with interventions around these possible periods.

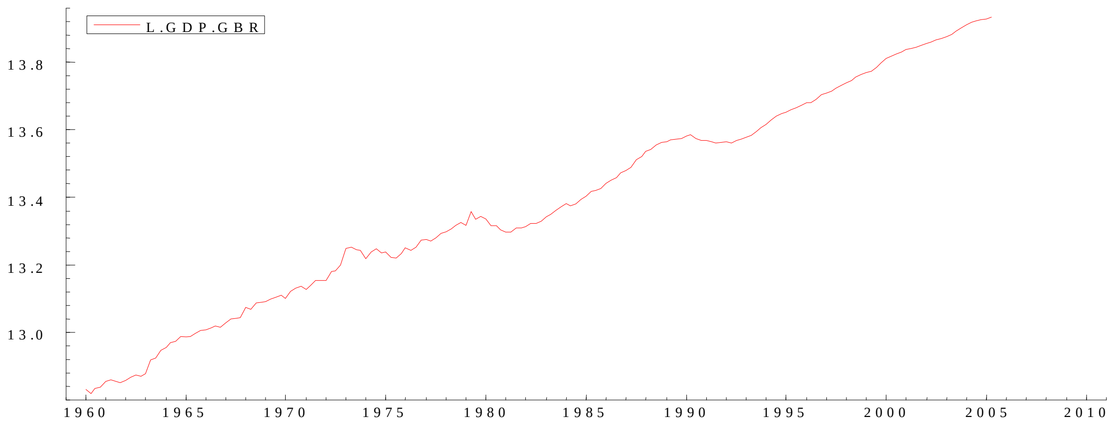

Figure 12. GBR GDP time series

The estimated model with a smooth trend, a cycle and interventions is,

L.GDP.GBR = Trend + Cycle + Level-shift1963.2 + Level-shift1973.1 + Outlier1979.2 + Irregular

For the seasonally adjusted GBR GDP data, STAMP detects three unusual movements in modeling process, an outlier in 1979.2 and two level shifts in 1963.2 and 1973.1. It is different from what we expected in advance, namely the year 1973 as outlier, and the year 1979 as level shift. Later, we will also examine the model with an outlier in 1973.1 and a level shift in 1979.2, and compare it with the current model. The estimated parameters for the model are shown in table 7, with coefficients of each variable, variances of disturbance, goodness of fit (Rd²) and prediction test (Prediction Failure Chi²).

Table 7. Estimated parameters for the GBR GDP structural time series model

Coefficient	Level	13.934**
	Slope	0.0066598**
	Cycle_1	(-) 0.0012134
	Cycle_2	(-) 0.0090102
	Lev1963.2	0.035360**
	Lev1973.1	0.046949**
	Irr1979.2	0.030774**
Variance of disturbance (q-ratio)	Level, σ_η^2	0
	Slope, σ_ζ^2	5.5863e-008 (0.0012)
	Cycle, σ_ψ^2	4.5636e-005 (1.0000)
	Iirregular, σ_ε^2	5.2375e-006 (0.1148)
Cycle	Variance, σ_κ^2	0.00057872
	Average length *(year)*	13.1184
	Frequency, λ	0.11974
	Damping factor, ρ	0.959762
Rd²		0.330
Prediction Failure Chi^2 (20)		1.62252(p-value: 1.0000)

* Statistically significant with 5% significance level, ** statistically significant with 1% significance level

Figure 13 shows the graphs of each component of the GBR GDP structural time series model.

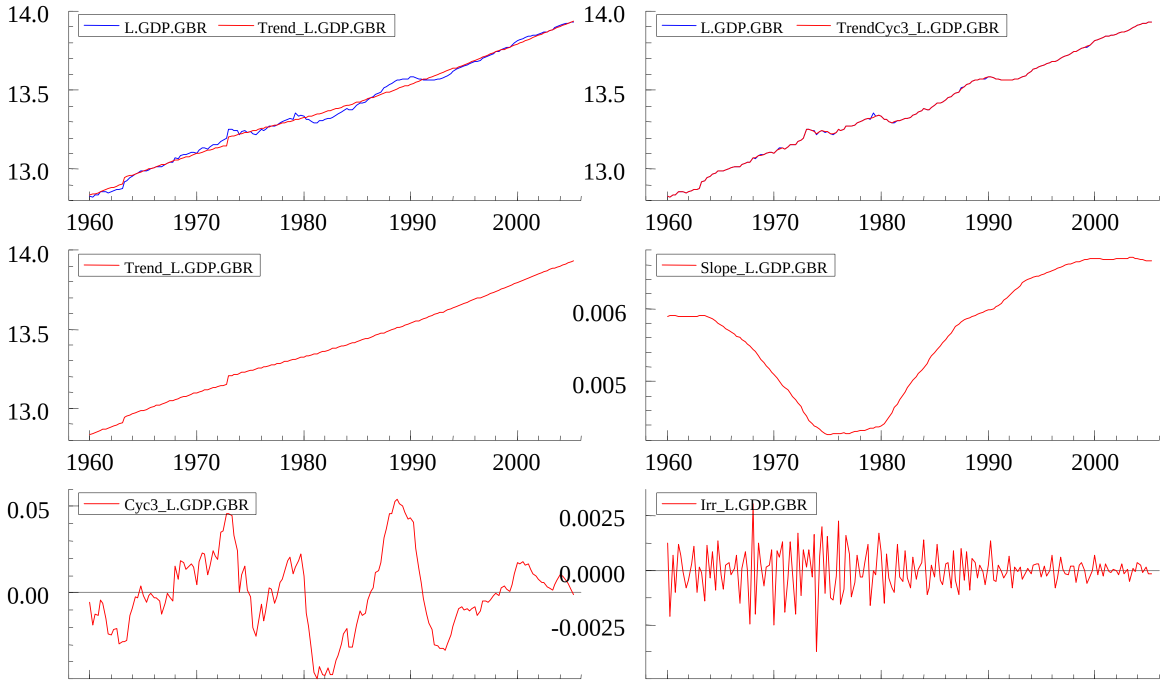

Figure 13. Components of the GBR GDP structural time series model

The q-ratio tells us that the cycle is the most stochastic among the slope, cycle and irregular components. Because of the small disturbance variance of the slope, the trend looks like deterministic. The coefficients for the interventions are statistically significant with 1% significant level. However, it is not clear if we can find 'the' reasons for the interventions. The early 60's were continued to be an expansion's period after the Second World War in GBR, and this may be the background for the positive level shift in 1963.2. The 70's were the troubled period with strikes, high inflation and low employment. The positive level shift in 1973.1 is, indeed, unreasonable with the information that we can get from the history. The outlier in 1979.2 may represent the election that Margaret Thatcher became the prime minister.

The average length of the cycle is 13.12 'years', which is long compared to other countries' cycle. The length of cycle seems to be longer after the peak in 1979 and the cycle seems to be less volatile from the middle of the 90's, which implies that GBR have experienced more stable economy from the middle of the 90's. It needs more study to examine the changes in cycle's length and volatility.

Different from the USA and the EURO-area cases, the disturbances of the irregular component is not zero in this model. This means that there are some movements, which cannot be explained by the model. We can also observe from the graph that the irregular component is more volatile in the 70's and much less volatile in after 90's, and it seems like the cycle component explains very well the recession in the 90's.

The model represents poorly in terms of interventions, since it is hard to find evidence of the positive level shift in 1973.1, and the cycle is too long compared to other countries. However, we choose the model because of two reasons. The first is the consistency of the model with other literatures. For example, according to Birchenhall *et al* (2000), there were three peaks and three troughs in GBR economy. They claim peaks in 1973.3, 1979.2 and 1990.2, and the troughs are 1975.3, 1981.1 and 1992.2. This matches to our model except that the STAMP reports the last peak around 1988.2. The first two recessions in the middle of the 70's and the beginning of the 80's were mainly caused by the first and second oil shocks, and the last recession came after the various domestic and international incidents, such as the new parliament after Thatcher and the first Gulf War.

The second reason for choosing this model is the forecast. With its less stochastic trend, the model forecasts an appropriate trend movement, which is shown close to a deterministic trend. We will examine the forecasts after the alternative model and compare both models' forecasts.

The application of the interventions and the long cycle are the model's shortcomings. Clearly, the use of interventions is somewhat arguable in this model. How do we use the interventions that STAMP reports, is considerably difficult when we don't have the particular events to support the interventions. A further problem is a proper positioning of the interventions. Sometimes STAMP detects unusual movements as both level shifts as well as outliers. It is our task to decide what the driving force of the unusual movement is, and it is important because we can get different models by various settings of interventions. With holding the restriction of a smooth trend, there are still questions about how we use the interventions.

To observe this, we build an alternative model for the GBR GDP with level shifts in 1963.2 and 1979.2 and outliers in 1973.1 and 1974.1, as we assumed after we saw the original graph in the beginning of the chapter. Since STAMP reports 1973.1 and 1979.2 as both level shift and outlier, we choose this combination for the alternative model. The outlier 1974.1 is detected during the modeling process, and it is fairly reasonable because it was three working day periods in GBR, which was initiated to reduce the energy use after the first oil shock. For convenience, we call the model above as 'model 1', and the alternative model as 'model 2'.

2.2.3.3 An alternative model, model 2

The estimated parameters for the model 2 are presented below.

Table 8. Estimated parameters for the GBR GDP structural time series model, model 2

Coefficient	Level	13.931**
	Slope	0.0047978
	Cycle_1	0.0017520
	Cycle_2	(-) 0.0026524
	Lev1963.2	0.031964**
	Irr1973.1	0.026235**
	Irr1974.1	(-) 0.026977**
	Lev1979.2	0.035612**
Variance of disturbance (q-ratio)	Level, σ_η^2	0
	Slope, σ_ζ^2	1.9214e-006 (0.1005)
	Cycle, σ_ψ^2	1.2276e-005 (0.6418)
	Iirregular, σ_ε^2	1.9128e-005 (1.0000)

Cycle	Variance, σ_{k}^{2} Average length *(year)* Frequency, λ Damping factor, ρ	0.000136343 5.4384 0.288834 0.953919
Rd²		0.28428
Prediction Failure Chi² (20)		1.98597 (p-value: 1.0000)

* Statistically significant with 5% significance level, ** statistically significant with 1% significance level

Figure 14 shows the graphs of each component of the model 2.

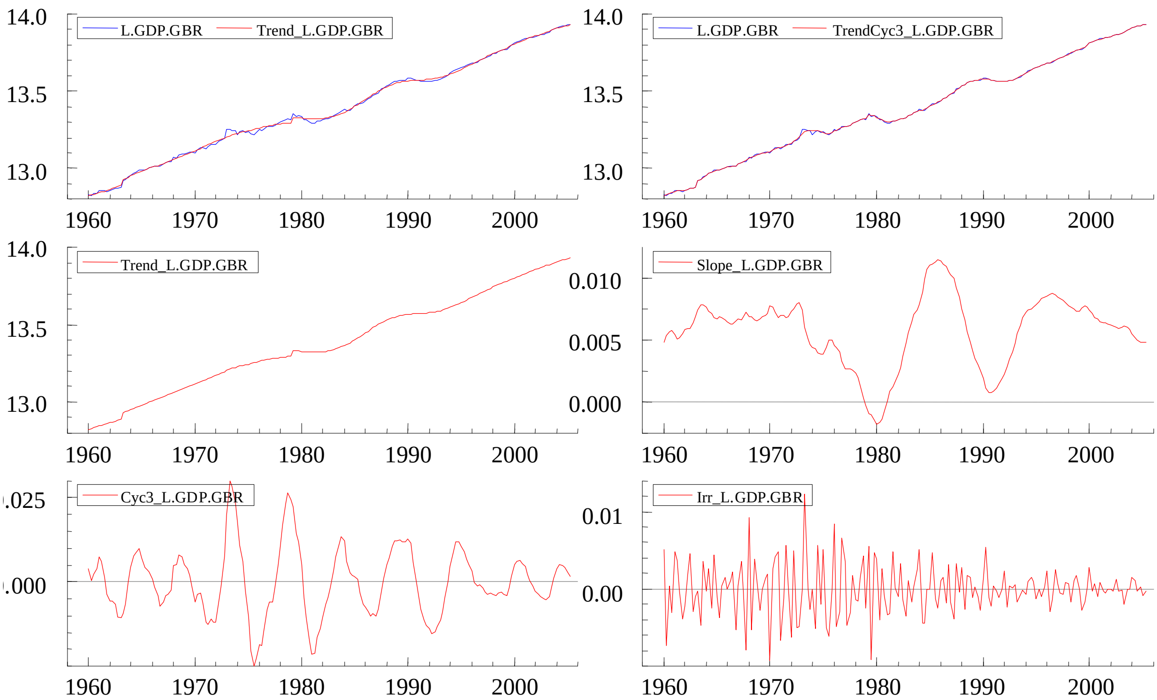

Figure 14. Components of the GBR GDP structural time series model, model 2

The fit of the model 2 is worse than the model 1 with smaller Rd². The variance of the irregular disturbance is bigger than the variance of the cycle disturbance, which means a small room for the stochastic cycle and greater unexplained part of the model. Because of the relatively high disturbance variance of the slope, the trend is more stochastic than the model 1. This model generates a shorter cycle with the length, 5.44 years. In addition to the cycle, this model seems to be appropriate in terms of the level shift in 1979.2. The positive coefficient of the dummy variable, Lev1979.2 may represent the Thatcher regime and her work to privatize of many public sectors. This might cause a short-term recession through strikes and high unemployment, but in the long run, it may cause a positive trend shift of the GBR economy.

To examine the differences in the cyclical movements, we plot a graph, which shows both cycles and a HP-filtered cycle with same data all together. That is in figure 15.

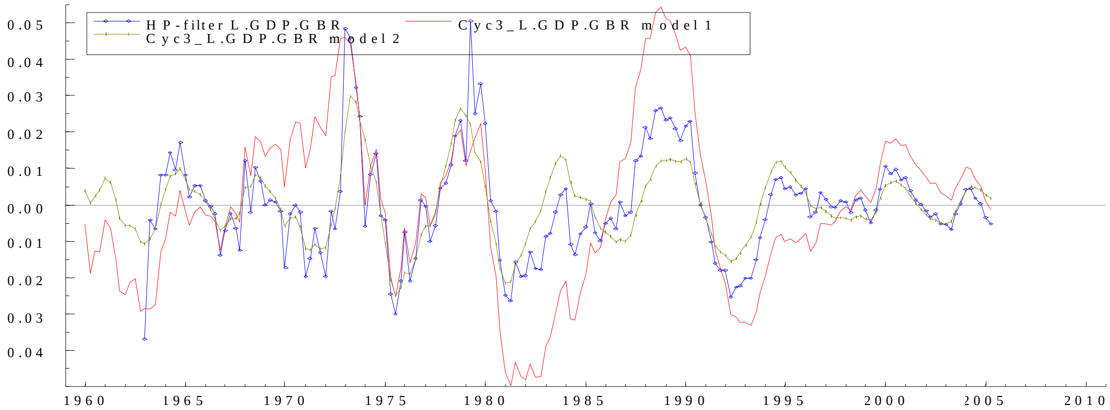

Figure 15. Cycles from the model 1, model 2 and HP-filtered cycle for the GBR GDP time series

We can see that the cycle from model 2 is similar to the HP-filtered cycle, whereas model 1's cycle is different. Having similar cycle to the HP-filter doesn't mean that the model 2 is better than the model 1, since HP-filter itself has been criticized for its spurious features. The question is then, what a cycle is, hence, a clear definition of a cycle. If it is as mentioned before, some movements which would repeat again and again over time, it will be difficult to understand that the relatively greater movement in model 1 will come back to the economy with similar attitude in the future.

The forecasts from the two models can be evaluated with the aid of figure 16.

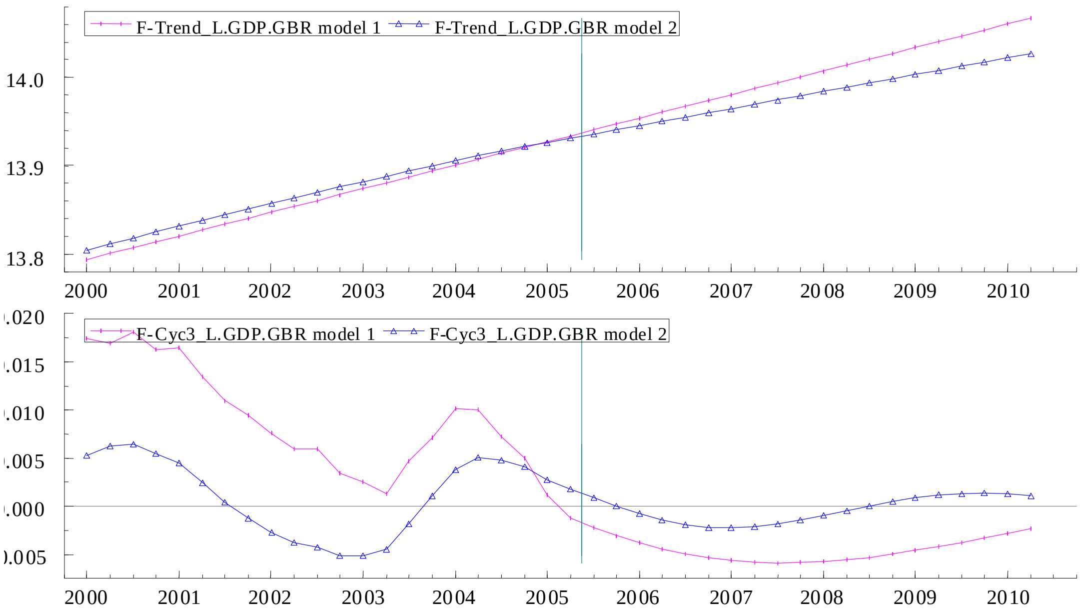

Figure 16. Trend forecasts (above) and the cycle forecasts (below), model 1 and model 2

The graph below in figure16 shows the two models' cycles. According to the model 1 and the model 2, the GBR is in recession period. The differences are the lengths of the cycle, or the forecasted troughs in both models. This gives a good example of the practical issues that often arise when forecasting with a STM, when we look at the above graph in figure16. The two curves are forecasted trends of model 1 and model 2. These represent the forecasted long-term movements of the GBR GDP. The model 2, with its shorter cycle, is more influenced by the most recent data observations. This results in forecasting the moderate growth of the trend. One may be misled by considering the components separately. With the combination of the trend and the cycle, we can however see that model 1 forecasts a higher growth than the model 2, even though the cycle of the model 1 forecasts a deeper and longer recession than the model 2.

Table 9 shows the forecasted annual GDP growth rates with OECD forecasted rates. It seems that the model 1 gives similar results as OECD does. Notice that all the models forecast a continuous growth of the GBR economy.

Table 9. Forecasted Real GDP growth rates, GBR. Source: SSB and OECD

Real GDP growth forecasting (annualized, %)											
		2005		2006				2007			
		Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
GBR	Model 1	2.3	2.3	2.4	2.4	2.5	2.5	2.6	2.6	2.6	2.7
	Model 2	1.7	1.6	1.6	1.7	1.7	1.8	1.9	2.0	2.0	2.1
	OECD	1.7		2.4				2.7			

2.2.4 Univariate GDP structural time series model, Sweden (SWE)

2.2.4.1 Data

We model the seasonally adjusted quarterly Swedish GDP time series from 1960.1 until 2005.2. It is the market volume in Swedish Krone (SEK), and chained at 2000 as the base year.

2.2.4.2 Modeling Swedish GDP time series

Figure 17 shows the Swedish GDP time series. From the graph, we see that the Swedish economy was growing relatively rapid until the beginning of the 70's. Through 70's until mid 80's, the growth was slowing down, and the GDP was more volatile than other periods. The

Swedish economy experienced a big recession in 1993, and after that it shows a stable growth pattern.

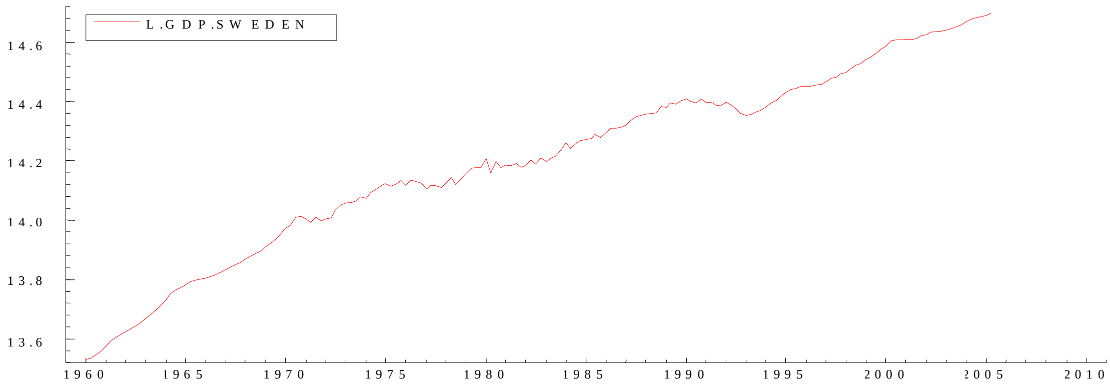

Figure 17. Swedish GDP time series

The estimated model with a smooth trend, a cycle and interventions is,

L.SWE.GBR = Trend + Cycle + Outlier1980.1 + Outlier1980.2 + Outlier1984.1 + Irregular

The estimated parameters for the model are shown in table 10, with coefficients of each variable, variances of disturbance, goodness of fit (Rd^2) and prediction test (Prediction Failure Chi^2).

Table 10. Estimated parameters for the Swedish GDP structural time series model

Coefficient	Level	14.701**
	Slope	0.0067448**
	Cycle_1	(-) 0.0027081
	Cycle_2	(-) 0.0052154
	Irr1980.1	0.025319**
	Irr1980.2	(-) 0.029158**
	Irr1984.1	0.022585**
Variance of disturbance (q-ratio)	Level, σ_η^2	0
	Slope, σ_ζ^2	2.9301e-007 (0.0056)
	Cycle, σ_ψ^2	5.2327e-005 (1.0000)
	Iirregular, σ_ε^2	6.5577e-006 (0.1253)
Cycle	Variance, σ_κ^2	0.000544037
	Average length *(year)*	12.6613
	Frequency, λ	0.124063
	Damping factor, ρ	0.950693
Rd^2		0.31479
Prediction Failure Chi^2 (20)		5.30764 (p-value: 0.9996)

* Statistically significant with 5% significance level, ** statistically significant with 1% significance level

The graphs of each component are presented in figure 18.

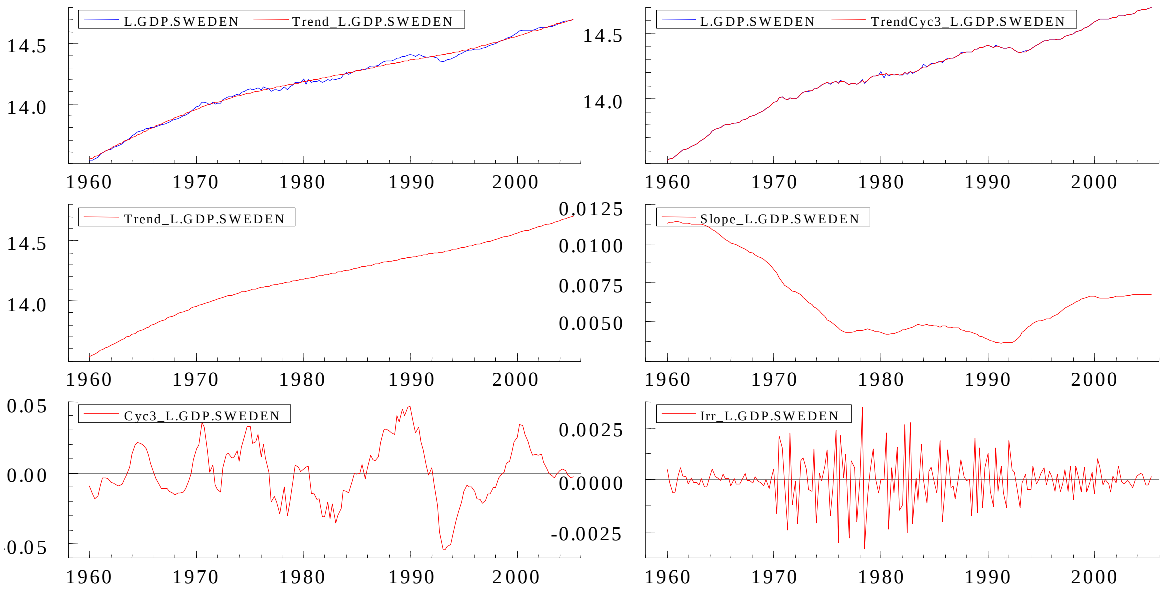

Figure 18. Components of the Swedish GDP time series

The variance of the slope component is small, and as a result, the trend is fairly smooth. The q-ratio of the slope is only 0.0056. The volatility of the GDP series in the 70's and 80's is reflected in the irregular component, showing high disturbances during the period. It is considered to be a failure in the Swedish monetary policy during this period (B. Sodersten, 2000). We can also observe that the Swedish economy is more stable after 1993 when the inflation-targeting regime was started in Sweden. The average length of the cycle is 12.66 years, which is quite long to generalize. However, it represents well the slowdown of the Swedish economy from 1976 to 1982, the Swedish Krone was devalued five times during this period. The cycle shows also the economic crisis in 1992-1993. All the detected interventions are outliers relating to the oil shocks and the devaluations. It is not clear to define the reason for the intervention with positive coefficient in 1980.1. It might be caused by the effect of the first minor devaluations in 1976-1977 of around 9 percent, which resulted in the short-term high productivity (low unit cost) within the industrial sector. Short after, the influence of the second oil shock caused record high real oil price in history (figure 19). The figure is taken from ‘The Swedish Economy’ (Aug. 2005). This may be the reason for the intervention with negative coefficient in 1980.2. The Swedish economy was still in severe problem with high inflation and poor performance of labor productivity, so the government devalued the Swedish Krone in 1981 of 10 percent, and in October 1982 of 16 percent. The effect of these aggressive devaluations resulted in the record high quarterly GDP growth rate of 1 percent in the first quarter of 1984, which is picked up by STAMP as a positive intervention coefficient.

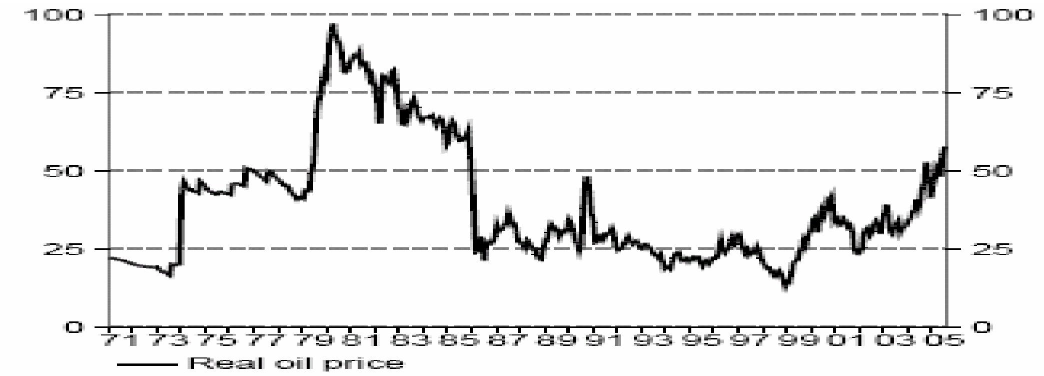

Figure 19. Real oil price in Sweden, (July 2005 = 57.6), Source: Swedish National Institute of Economic Research (NIER)

Figure 20 shows the model's forecasts.

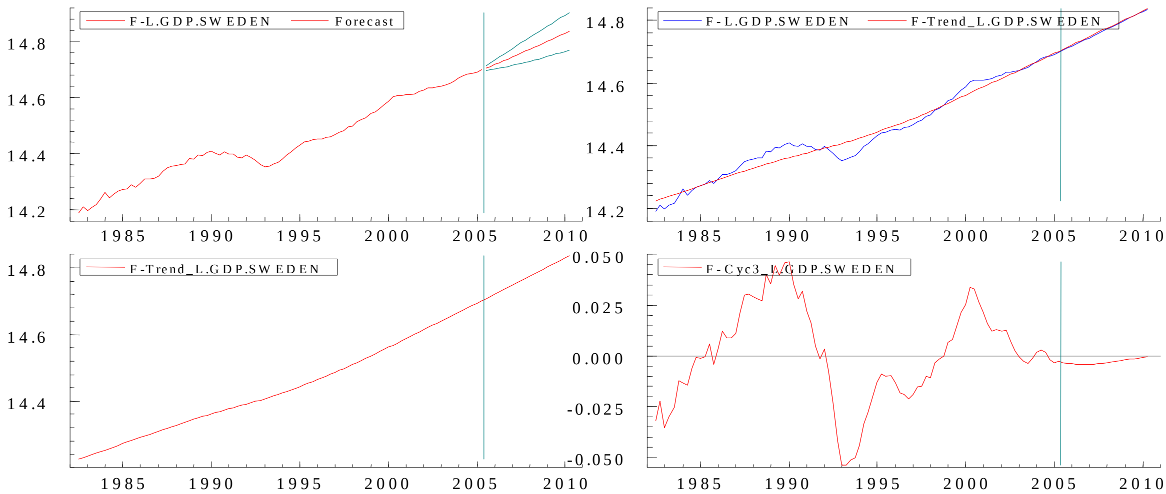

Figure 20. Forecasts for the Swedish GDP structural time series model

As we can see, the overall GDP is forecasted to grow rapidly, but the driving force for the growth is shown to be the trend growth, not the cyclical movement. Since the trend is generated to be less stochastic in this model, the rapid growing pattern after the deep recession in 1993 continues in the future. The cyclical movement in the model is forecasted to be slightly under the trend, which we should be careful to interpret. If we only focus on the cyclical movement, then we will miss the information from the trend forecast, which will lead us to misunderstand the whole situation. After all, the model forecasts strong growth of the Swedish economy in near future. According to ‘The Swedish Economy’ (Dec. 2005), the trend (the potential GDP) is revised upward because of the strong household consumption,

export as well as the forecasted low ill health. This may explain the forecasting graphs above, with high growth in trend and slight recession in cycle.
Table 11 shows the forecasted annual GDP growth rates with OECD forecasted rates.

Table 11. Forecasted Real GDP growth rates, Sweden. Source: SSB and OECD

Real GDP growth forecasting (annualized, %)											
		2005		2006				2007			
		Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
SWE	STM	2.5	2.6	2.6	2.6	2.7	2.7	2.7	2.7	2.8	2.8
	OECD	2.4		3.5				3			

While OECD forecasts a rapid growth in 2006 and slowing down in 2007, the STM forecasts a moderate but continuous growth for the Swedish economy. As we see from figure 19, this continuous growth is mainly caused by the trend growth.

2.2.5 Univariate GDP structural time series model, Japan (JPN)

2.2.5.1 Data

We model the seasonally adjusted quarterly Japanese GDP time series from 1960.1 until 2005.2. It is the market volume in Japanese Yen (JPY), and chained at 2000 as the base year.

2.2.5.2 Modeling Japanese GDP time series

The Japanese economy has developed differently from other developed countries. The reactions of the Japanese economy to the domestic and international shocks are considered to be less extreme than other western countries. For example, the rapid growth just after the Second World War was slowed down when the first oil shock hit the global economy as other countries. However, the Japanese economy managed to grow at average 5 percent per year even after the first oil shock. The inflation level, unemployment rate and the interest rate have been unusually low in Japan through history (M. Sharpe, 2004). Since we aware the difference of the Japanese economy, it is interesting to see how STAMP models the Japanese economy and compare it with other country's cases.

Figure 21 shows the Japanese GDP. From the graph, we see that the Japanese economy was growing rapidly through the 60's to the middle of 70's, and then the growth slows down until the end of the 80's. The growth became even slower from the 90's, and the Japanese economy remains at the similar growth level since then.

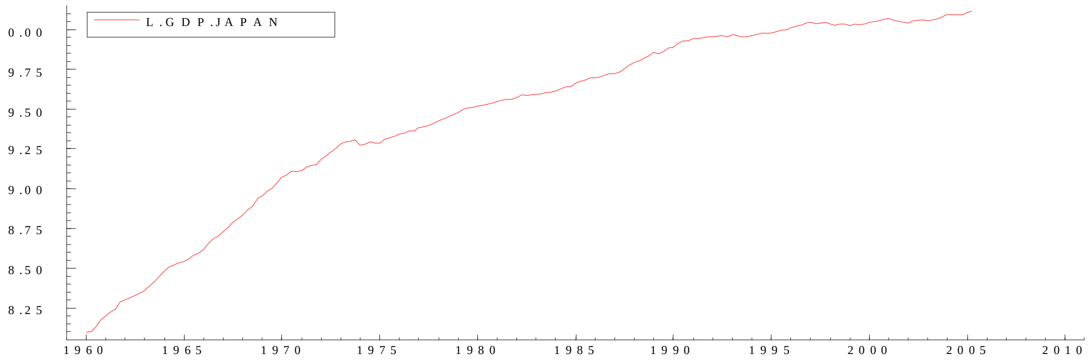

Figure 21. Japanese GDP time series

The estimated model with a smooth trend, a cycle and intervention is,

L.JPN.GBR = Trend + Cycle + Lev1974.1 + Irregular

The estimated parameters for the model are shown in table 12, with coefficients of each variable, variances of disturbance, goodness of fit (Rd²) and prediction test (Prediction Failure Chi²).

Table 12. Estimated parameters for the Japanese GDP structural time series model

Coefficient	Level	20.112**
	Slope	0.0064778*
	Cycle_1	0.0026926
	Cycle_2	0.0024171
	Lev1974.1	(-) 0.045100**
Variance of disturbance (q-ratio)	Level, σ_η^2	0
	Slope, σ_ζ^2	2.7357e-006 (0.0927)
	Cycle, σ_ψ^2	2.9525e-005 (1.0000)
	Iirregular, σ_ε^2	1.1377e-005 (0.3853)
Cycle	Variance, σ_κ^2	0.000115636
	Average length *(year)*	4.47096
	Frequency, λ	0.351333
	Damping factor, ρ	0.862945
Rd²		0.42889
Prediction Failure Chi² (20)		21.7942 (p-value: 0.3518)

* Statistically significant with 5% significance level, ** statistically significant with 1% significance level

The graphs of each component are presented in figure 22.

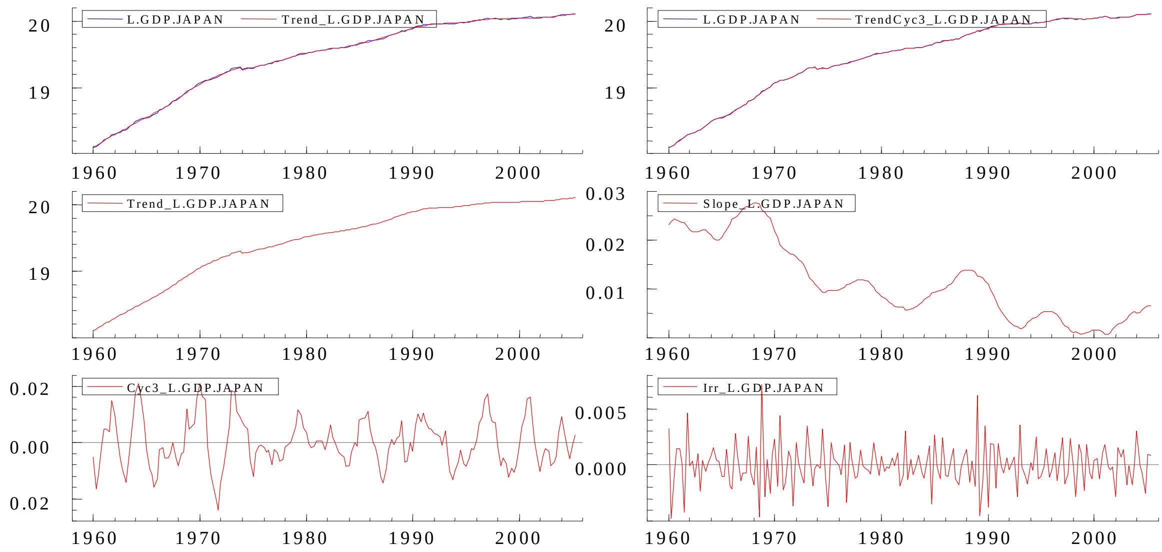

Figure 22. Components of the Japanese GDP structural time series model

The trend is highly stochastic and is representing the changes of long-term movement around 1974 and 1990. The slope varies through the periods, but also shows negative development over time, which matches well with the trend. The q-ratios tell us that the cycle explains most of the model's variation, and the irregular component graph shows that there may be possible breaks around 1968 and 1989. These might be possible interventions, which STAMP doesn't capture, and we will come back to this in the alternative model for the Japanese GDP time series. STAMP reports an intervention for the Japanese GDP time series, namely the level shift in 1974.1 caused by the first oil shock. It is referred to be a permanent reduction of the Japanese growth rate. The Japanese economy hasn't recovered to the growth level it achieved before the first oil shock again. The cycle is short with average length of 4.47 years.

One point that we should mention about the model above is the *Prediction Failure Chi*^{2} test. All the other models that we have built showed the p-value to be close to unity. However, the Japanese GDP model shows the p-value around 0.35. This doesn't mean that the model rejects the null hypothesis, but this may imply that the model forecasts poorly. Figure 23 shows the model's post-period prediction, and we can see that the post-period prediction curve doesn't match well to the actual GDP curve, even though it lies within the prediction intervals.

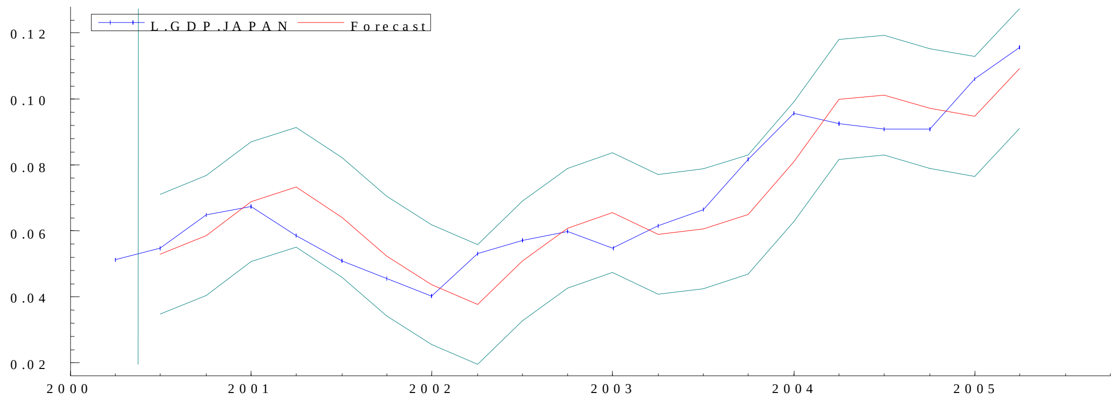

Figure 23. Post-period prediction for the Japanese GDP time series, 2000.2 - 2005.2

Figure 24 represents the forecasts for the trend and cycle.

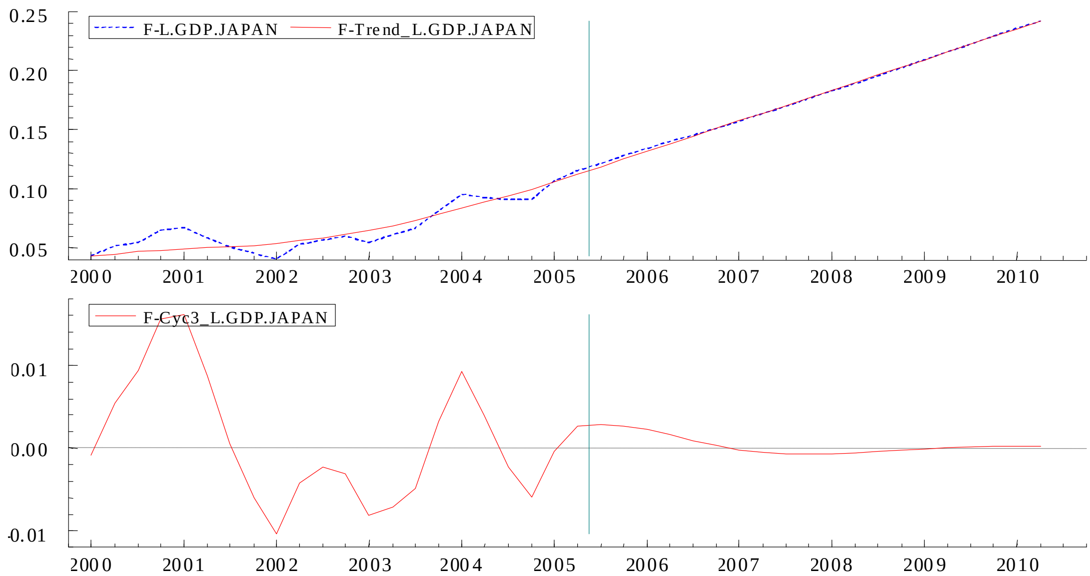

Figure 24. Forecasts for the trend and cycle, the Japanese GDP structural time series model

From the first graph, we see the influence of the short cycle shifts the trend up in 2002.3. This results in the rapid growth in the trend forecast. Regarding the cyclical component, the Japanese economy is considered to have passed the peak in 2005.3. Now the economy is slowdown but with moderate change.

The model above shows relatively reasonable features about the Japanese GDP development. However, with its short cycle, the trend forecast may be exaggerated, showing too high growth in near future. According to Sharpe (2002), the Japanese economy was in recession from 1980.1 to 1983.1, the longest recession since June 1951. Sharpe (2002) also says that the Japanese economy had a very strong boom from 1986.4 to 1991.1, the second longest expansion after the late 60's. The model above supports these poorly with weak recession and expansion around these periods. Moreover, the model doesn't include the possible level shift around 1990, which is represented in figure 21. Thus, we build an alternative model, which may be proper for the Japanese GDP time series. For convenience, we call the model above as 'model 1', and the alternative model as 'model 2'.

2.2.5.3 An alternative Japanese GDP structural time series model, model 2

The alternative model includes another level shift in 1989.2. STAMP doesn't report this period as intervention, it explains this period with high disturbances in the irregular component. The late 80's is called 'the bubble period' in the Japanese economy. The generous monetary policy pursued by the Bank of Japan made an unusual combination between the goods market and the asset market. The low inflation rate at average 1.1 per cent combined with the low interest rate (the call rate fell from the high of 8.0 in December 1985 to the low of 3.2 per cent in May 1988) caused the high stock prices and land prices, Sharpe (2002). People took loans to invest on the asset and land market. The bubbles started to collapse in 1989 followed by the worst financial crisis in the post war decades in the 90's. With the historical background, the level shift with negative coefficient in 1989.2 is reasonable in modeling the Japanese GDP time series.

Table 13 shows the variances of disturbances and cycle component. To compare the results, we put the result from model 1 besides.

Table 13. Estimated parameters for the Japanese GDP structural time series model, model 1 & model 2

		Model1 (with Lev1974.1)	Model2 (with Lev1974.1 & Lev1989.2)
Variance of disturbance (q-ratio)	Level, σ_η^2	0	0
	Slope, σ_ζ^2	2.7357e-006 (0.0927)	1.7805e-006 (0.0337)
	Cycle, σ_ψ^2	2.9525e-005 (1.0000)	5.2824e-005 (1.0000)
	Irregular, σ_ε^2	1.1377e-005 (0.3853)	2.2903e-006 (0.0434)
Cycle	Variance, σ_κ^2	0.000115636	0.000342254
	Average length *(year)*	4.47096	9.44807
	Frequency, λ	0.351333	0.166256
	Damping factor, ρ	0.862945	0.919597
Rd^2		0.42889	0.45733
Prediction Failure Chi^2 (20)		21.7942 (p-value: 0.3518)	16.7302 (p-value: 0.6704)

We see that the model 2 generates a little less stochastic trend caused by the small variation of the slope component. The cyclical component explains greater part of the model's variation, resulting the longer cycle with 9.45 years. We can also notice that the p-value for the *Prediction Failure Chi²* test is higher in model 2 with 0.67, showing the improvement of the post-period prediction.

Figure 25 shows the components of the model 2.

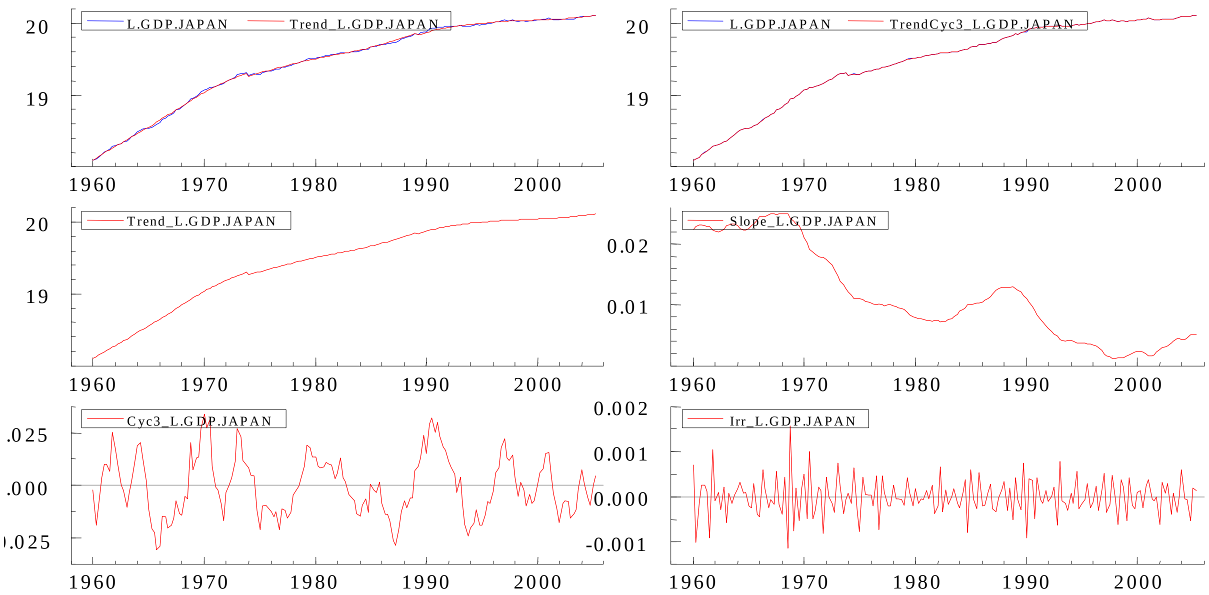

Figure 25. Components of the Japanese GDP, model 2

The cyclical movement matches well with Sharpe's arguments. A sharp boom in 1973 resulted in land speculation collapsed in 1974. The cycle shows well the second longest recession from 1980.1 to 1983.1, and the second longest expansion from 1986.4 to 1991.2. The cycle seems to be long but reasonable.

Figure 26 represents the trend forecasts and the cycle forecasts for the Japanese GDP of model 1 and model 2.

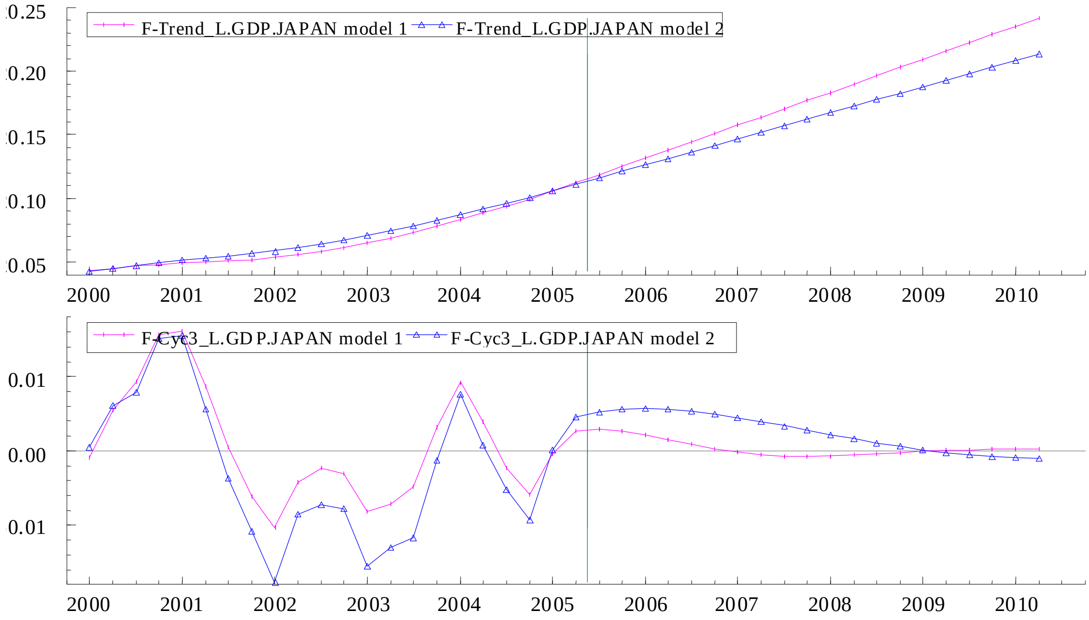

Figure 26. Trend forecasts (above) and the cycle forecasts (below), model 1 and model 2

From previous analysis, we know that the model 1 generates more stochastic trend with shorter cycle than the model 2. As a result, the model 1 tends to follow the most recent period's development in forecasting, which is shown in the graph above. The trend grows rapidly, and the cycle's amplitude is small in the model 1. The model 2 forecasts a moderate growth of the trend component, with greater and longer cyclical movement.

Table 14 shows the forecasted annual GDP growth rates with OECD forecasted rates.

Table 14. Forecasted Real GDP growth rates, Japan, source: SSB and OECD

Real GDP growth forecasting (annualized, %)											
		2005		2006				2007			
		Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
JPN	Model 1	2.3	2.5	2.4	2.3	2.3	2.3	2.4	2.5	2.5	2.6
	Model 2	2.2	2.2	2.1	2.0	1.9	1.9	1.9	1.8	1.8	1.8
	OECD		1.7	1.9	2.1	1.9	2	2	2.1		

The forecasted annual growth rates are overall similar for the three models. With its high growth in trend, the model 1 shows a continuous growth of the Japanese economy. On the other hand, with its moderate growth in trend, the model 2 shows a smaller growth rate in near future. But both models forecast stable growth of the Japanese economy, which is same in the OECD forecast.

3. Multivariate structural time series model

3.1 Introduction

Seemingly unrelated time series equations (SUTSE) are applied for equations with several time series, ($\boldsymbol{y}_t$), and unobserved components (trend, seasonal, cycle and irregular). Each component is vectors and the correlations of disturbances are the link across different series. The basic modeling process is similar to the univariate model. In addition to the univariate model, we concern the correlations between each component's disturbances and build relationships of each component resulting from the correlations. In our thesis, with the GDP time series in USA, EURO-area, GBR, Sweden and Japan, we start from building a multivariate model. As we will observe later, the multivariate model shows complicated outcomes, which may lead us to incorrect interpretations. Thus, we will briefly get through the multivariate model, and then we will move to the bivariate models and their interpretations. The bivariate models are the main concern of the thesis. The reasons to limit the process to bivariate models are first; to avoid complications and spurious cycles of multivariate modeling and second; to compare our result to one by Benedictow and Johansen (2005). In their article, which is published by Statistics Norway (SSB), Benedictow and Johansen present the cyclical correlations of several European countries against the USA cycle. They use the HP-filter to generate the cycles. As it is mentioned earlier, one of the main concerns of this thesis is to examine the applicability of STM, and by comparing our result to theirs, we may find out the answer. As a result, our main purpose is to investigate the degree of correlations as well as the lagging/leading relationships of each cycle against USA cycle. The USA economy is leading the world's economy, and we can investigate if it is also supported by STM.

Besides the co-movements of the cycles (common cycles), it is also possible to use STM for investigating co-movements of the long-term growth (common trends) with the GDP time series. Recently, there are many studies about convergences in economy within G7 or European countries. Harvey and Mills (2005), Carvalho and Harvey (2002), Carvalho and Harvey (2004), Luginbuhl and Koopman (2004) and Carvalho et al. (2006) are all showing convergences within their sample series. The difference is that they use GDP per capita for their study, while we have real GDP time series. In my point of view, it is not a point to investigate a possible common trend in GDP time series, because the size of each GDP is simply not comparable. For example, the US GDP is much bigger than the Swedish GDP with different factors involved; in this case, what can we learn from investigating a common trend within the two economies? Or if there is a common trend, what does it actually mean? However, when it comes to the GDP per capita, the common trend and convergence mean that the individuals' income level within the two economies has been converged. This may imply that the difference of life quality has been reduced. It is also very interesting application of STM, however, we limit our thesis to the bivariate models and the cyclical correlations against USA cycle.

The seasonally adjusted log GDP, quarterly market volume from OECD is used for the analysis, same as for the univariate model. STAMP is used for the bivariate modeling, and PcGive is used for the correlations between each series and their lags. Excel is used for the simple correlation graphs.

3.2 Components of multivariate structural time series model

In a multivariate model, we have N time series, the vector $\boldsymbol{y}_t$ is,

$\boldsymbol{y}_t = (y_{1t}, y_{2t}, \ldots, y_{Nt})'$,

the trend, cycle and irregular components are respectively,

$\boldsymbol{\mu}_t = (\mu_{1t}, \mu_{2t}, \ldots, \mu_{Nt})'$, $\boldsymbol{\psi}_t = (\psi_{1t}, \psi_{2t}, \ldots, \psi_{Nt})'$, $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{Nt})'$,

then , the multivariate STM (Structural Time series Model) will be,

$\boldsymbol{y}_t = \boldsymbol{\mu}_t + \boldsymbol{\psi}_t + \boldsymbol{\varepsilon}_t, \quad t = 1, \ldots, T, \quad \boldsymbol{\varepsilon}_t \sim NID(0, \boldsymbol{\Sigma}_\varepsilon)$,

where $\boldsymbol{\Sigma}_\varepsilon$ is an $N \times N$ positive semi-definite matrix. The trend is

$\boldsymbol{\mu}_t = \boldsymbol{\mu}_{t-1} + \boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim NID(0, \boldsymbol{\Sigma}_\eta)$

$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \boldsymbol{\zeta}_t, \quad \boldsymbol{\zeta}_t \sim NID(0, \boldsymbol{\Sigma}_\zeta)$,

with $\boldsymbol{\Sigma}_\eta = 0$, we get the smooth trend model (fixed levels plus stochastic slopes). With $\Sigma_\zeta = 0$ and $\boldsymbol{\Sigma}_\eta \neq 0$, we get the random walk plus drift (fixed slopes plus stochastic levels).
The cycles in the unrestricted model[1] are similar cycles.

[1]Unrestricted model: the system doesn't force to have a reduced rank of the covariance matrix of each component disturbances. For cycles, the covariance matrix of cycles will have full rank. The cycles generated by an unrestricted model are called similar cycles. Restricted model: we restrict the rank of the covariance matrix to be less than full rank, hence, the covariance matrix will have linear combinations according to the rank. By this, we can force the model to have common features such as a common trend and a common cycle.

According to Harvey and Koopman (1997), the similar cycles are obtained by constraining the damping factor and the frequency, ρ and λ_c, to be the same in all series. The similar cycle is

$$\begin{pmatrix} \boldsymbol{\psi}_t \\ \boldsymbol{\psi}^*_t \end{pmatrix} = \left(\rho \begin{pmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{pmatrix} \otimes \mathbf{I}_N \right) \begin{pmatrix} \boldsymbol{\psi}_{t-1} \\ \boldsymbol{\psi}^*_{t-1} \end{pmatrix} + \begin{pmatrix} \boldsymbol{k}_t \\ \boldsymbol{k}^*_t \end{pmatrix}, \quad t = 1, ..., T$$

where $\boldsymbol{k}_t$ and $\boldsymbol{k}^*_t$ are $N \times 1$ vectors of disturbances such that

$E\,(\boldsymbol{k}_t\,\boldsymbol{k}_t') = E\,(\boldsymbol{k}^*_t\,\boldsymbol{k}^*_t') = \boldsymbol{\Sigma}_k,\;\; E(\boldsymbol{k}_t\,\boldsymbol{k}^*_t') = 0,$

where $\boldsymbol{\Sigma}_k$ is a $N \times N$ covariance matrix. Carvalho and Harvey (2004) say that the model allows the disturbances to be correlated across the series. The cycles of different series will have same properties, since the damping factor and the frequency, ρ and λ_c, are same in all series. The cycles will have same length (because of the same frequency), and their movements are centered around the same periods. If we presume that these economies are hit by similar shocks, such as the oil shocks during the 70's, the similar cycles are reasonable tools to examine the effect of the shocks. Based on this assumption, we will investigate if there are cyclical correlations within different series. However, we have to remember that causes of the cyclical movements can be either the global shocks or the country-specific shocks. A global shock implies a shock, which influences on several economies; the oil price may be a good example of a global shock. A country-specific shock is a shock caused by domestic reasons, such as political shifts, natural disasters or strikes. Monfort *et al.* (2002) call this 'common shocks (global shocks) vs. spillover shocks (country-specific shocks)'.

We see the driving forces of cyclical movements to be either common shocks or country-specific shocks or both. Thus the common cycle model of Engle and Kozicki (1993) that assumes a perfect correlation between cycles applies too strong restriction. By restricting the rank of the covariance matrix to have a linear combination, we can obtain a common cycle, but in this thesis, we limit the cyclical movement to have similar cycles. In this instance, the cycles are moving similarly resulting from the same damping factor and the same frequency, but not having a perfect correlation.

3.3 Multivariate GDP time series model

We build a multivariate model with the five areas' GDP. The smooth trend (fixed levels plus stochastic slopes) is applied as the univariate model. The interventions, which are detected by the auxiliary residual function in STAMP, are used for the model. No restrictions are applied in the modeling process; this means that the covariance matrices of level, slope and cycle have full ranks. Similar cycles are generated under constraints of the same damping factor and frequency. A multivariate model gives useful information about the correlations of each component disturbances through irregular, slope and cycle covariance matrices.

The multivariate model with these five areas' GDP time series is

$\boldsymbol{y_t}$ = **Trend** + **1 Cycle(s)** + **Interventions** + **Irregular**
y_{1t} = Log GDP USA
y_{2t} = Log GDP EURO-area
y_{3t} = Log GDP GBR
y_{4t} = Log GDP Sweden
y_{5t} = Log GDP Japan

The estimated covariance matrices of disturbances are presented below. The bold numbers are representing correlations. The covariance matrix of irregular ($\boldsymbol{\Sigma}_\varepsilon$), slope ($\boldsymbol{\Sigma}_\zeta$) and cycle ($\boldsymbol{\Sigma}_k$) are,

$$\boldsymbol{\Sigma}_\varepsilon = \begin{pmatrix} 1.0117e\text{-}005 & \mathbf{-0.93670} & \mathbf{0.081540} & \mathbf{-0.13421} & \mathbf{-0.14016} \\ -1.1483e\text{-}005 & 1.4854e\text{-}005 & \mathbf{0.022247} & \mathbf{0.25793} & \mathbf{0.18670} \\ 1.3132e\text{-}006 & 4.3414e\text{-}007 & 2.5637e\text{-}005 & \mathbf{0.53459} & \mathbf{-0.64923} \\ -7.1133e\text{-}007 & 1.6564e\text{-}006 & 4.5102e\text{-}006 & 2.7764e\text{-}006 & \mathbf{-0.18875} \\ -1.9486e\text{-}006 & 3.1451e\text{-}006 & -1.4369e\text{-}005 & -1.3747e\text{-}006 & 1.9106e\text{-}005 \end{pmatrix}$$

$$\boldsymbol{\Sigma}_\zeta = \begin{pmatrix} 6.4292e\text{-}007 & \mathbf{-0.43804} & \mathbf{0.46125} & \mathbf{0.61431} & \mathbf{-0.20613} \\ -2.0529e\text{-}007 & 3.4162e\text{-}007 & \mathbf{0.42146} & \mathbf{0.20186} & \mathbf{0.35893} \\ 3.6135e\text{-}007 & 2.4068e\text{-}007 & 9.5461e\text{-}007 & \mathbf{0.79943} & \mathbf{0.15037} \\ 2.4674e\text{-}007 & 5.9099e\text{-}008 & 3.9126e\text{-}007 & 2.5092e\text{-}007 & \mathbf{0.091923} \\ -1.7785e\text{-}007 & 2.2575e\text{-}007 & 1.5809e\text{-}007 & 4.9550e\text{-}008 & 1.1580e\text{-}006 \end{pmatrix}$$

$$\boldsymbol{\Sigma}_k = \begin{pmatrix} 3.4689e\text{-}005 & \mathbf{0.93046} & \mathbf{0.21617} & \mathbf{0.10982} & \mathbf{0.080816} \\ 1.5105e\text{-}005 & 7.5968e\text{-}006 & \mathbf{0.26518} & \mathbf{0.12205} & \mathbf{0.12796} \\ 6.6519e\text{-}006 & 3.8186e\text{-}006 & 2.7295e\text{-}005 & \mathbf{-0.13395} & \mathbf{0.37683} \\ 4.8990e\text{-}006 & 2.5480e\text{-}006 & -5.3005e\text{-}006 & 5.7369e\text{-}005 & \mathbf{-0.081113} \\ 1.8184e\text{-}006 & 1.3473e\text{-}006 & 7.5210e\text{-}006 & -2.3470e\text{-}006 & 1.4594e\text{-}005 \end{pmatrix}$$

By observing the correlations, we may obtain the information of the multivariate model. The important points are

- The negative correlation of irregular disturbance between USA and Euro-area, -0.93670, says that there might be some common movement within only these two areas, which is not explained by the model.
- The correlations of irregular disturbance between GBR with Sweden and Japan are, respectively, -0.53459 and 0,64923. This may imply that there are possible co-movements within these areas, which are not explained by the model.
- The slope covariance matrix may show the relatively high correlations between areas excluding Japan. This may imply that there exist correlations for the growth in the long-term movement.
- The correlations of the cycle disturbances are not easy to interpret. The correlation between USA and Euro-area is 0.93046, which implies very high correlations with the disturbance through all the periods. It is not so convincing that other areas have so low cyclical correlations as it is shown in the covariance matrix. Especially, the low correlation of Japan with USA, 0.080816, which means almost no cyclical correlation between two countries, is not supportable.

Figure 27 shows the similar cycles of the multivariate model.

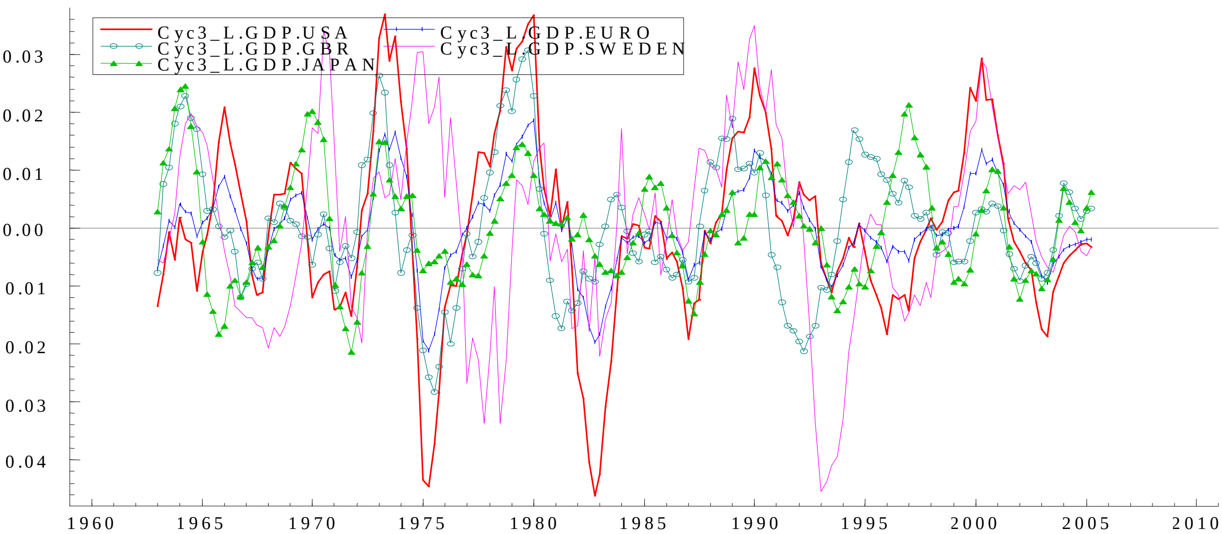

Figure 27. Similar cycles of the multivariate model

The similar cycles show same negative reactions after the first oil shock, excluding the Swedish cycle. The Japanese, Swedish and GBR cycles are somewhat different in their movements, especially in the 90's. It is not easy to define the cyclical relationships between countries from the graph above. It is because of the inconsistent correlations through time and the lagging/leading relationships between areas. To examine the lagging/leading relationships, we specify the lags of each cycle and investigate the cyclical correlations of the lagged cycles[2]. Figure 28 shows the cyclical correlations of Euro-area, GBR, Sweden and Japan against USA cycle. To compare the result to Benedictow and Johansen (2005), we draw the cyclical correlations against the USA cycle.

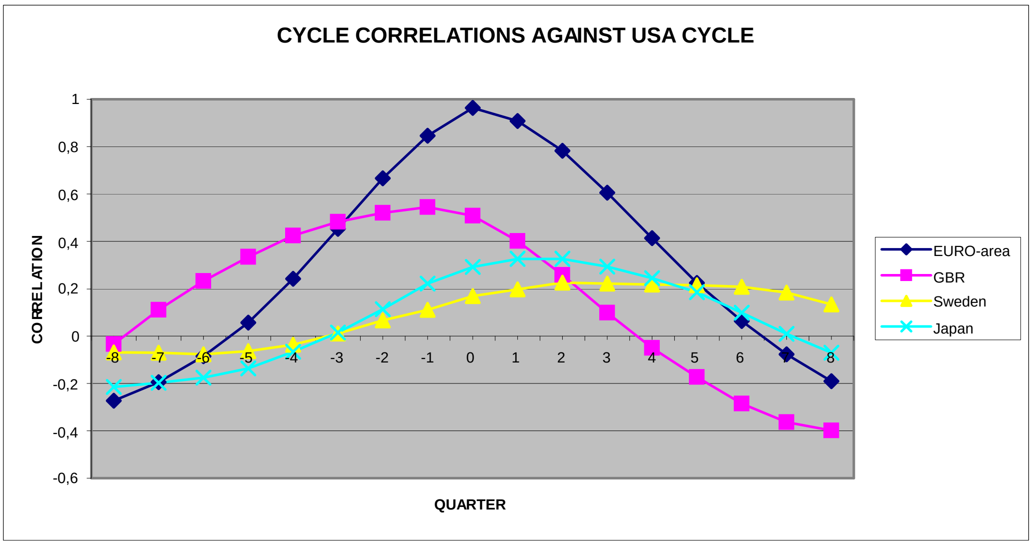

Figure 28. Cyclical correlations against USA cycle, multivariate model

The information that figure 28 provides us is incorrect in many ways. The Euro-area cycle tells that when the USA economy hit the top, the Euro-area's economy will show the same development with same extent, without any delay. It also says that the GBR cycle is leading the USA cycle, which is very difficult to support. The reason why the multivariate model gives such arguable information is over the extent of this project. A possible answer may be the interaction within the system, which makes a series be influenced by others that are actually not related. This will be more clear especially when the size of the economies are very different like the case above. Another point to concern is the sensitivity of the model. The result will be different if we add other series into the model or remove series from the

[2] The process is carried out manually. STAMP does not have a function to find out the lagged cross correlations. Thus, we have to save the cyclical component separately, and then use PcGive to carry out the correlation analysis. This might be a weak point of STAMP.

model or vary the length of the time series. This implies that the result might not be credible, and the choice of variables should carefully be evaluated before the actual modeling process.

To avoid such consequences, we move to the bivariate model.

3.4 Bivariate GDP structural time series model

Possible cyclical correlations against USA cycle are examined for Euro-area, GBR, Sweden and Japan. The main purpose is to find out cyclical correlations when we allow the disturbances of each component to be correlated, hence, building STMs (Structural Time Series models). In addition, we will experiment the suitability of a STM to generate cycles compare to other traditional cycle generating methods, such as HP-filter. For doing this, we will generate similar cycles by STM and compare the results with Benedictow and Johansen (2005), which shows the cyclical correlations between countries against the USA cycle by HP-filter. The figure below is taken from their article.

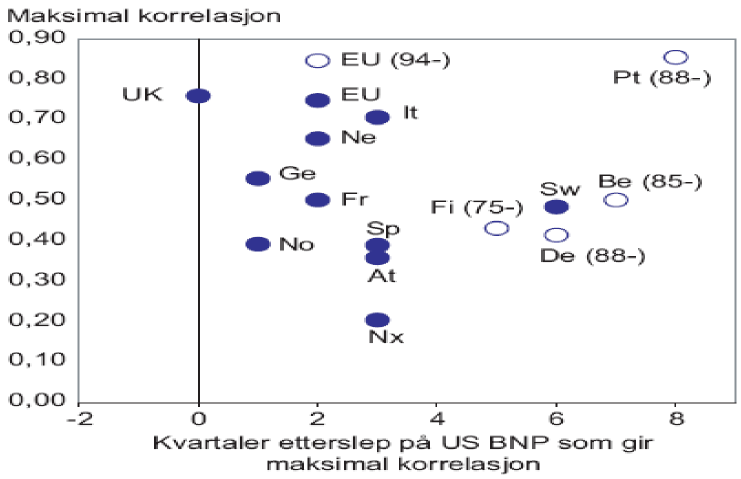

Figure 29. European countries' cyclical correlation against USA (1971-) source: Statistics Norway (data from OECD)

We see that the EU cycle is lagging by 2 quarters with correlation around 0.75, and the GBR (UK) is no lagging with correlation around 0.75. The Swedish cycle shows 6 quarters lagging with 0.5 correlation. It is interesting to compare the graph above to our model (STM) and find out if STM function suitably for generating business cycles. One of the reasons for the wide use of HP-filter is its convenience and simplicity. Thus many economists use HP-filter, even though it may generate spurious cycles (Harvey and Jaeger (1993)). If a STM can generate suitable cycles without spurious cycles, it will be very useful for further application for business cycles, since STM has its advantages like directly interpretable components, forecasting as well as its convenience and simplicity.

We apply the smooth trend model (fixed levels plus stochastic slopes) with full rank for covariance matrix to generate similar cycles.

3.4.1 Bivariate GDP structural time series model, USA and Euro-area

The model is

$\boldsymbol{y}_t$ = Trend + 1 Cycle(s) + Interventions + Irregular

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} 16.223 \\ 15.807 \end{pmatrix} \boldsymbol{\mu}_{t-1} + \begin{pmatrix} 0.0081 \\ 0.0033 \end{pmatrix} \boldsymbol{\beta}_{t-1} + \begin{pmatrix} 0.007 \\ 0.008 \end{pmatrix} \boldsymbol{\psi}_t + \begin{pmatrix} -0.019 \text{ Irr1970.4} + 0.031 \text{ Lev1978.2} \\ -0.028 \text{ Irr1968.2} + 0.042 \text{ Lev1991.1} \end{pmatrix} + \boldsymbol{\eta}_t + \boldsymbol{\varepsilon}_t$$

y_{1t} : Log GDP USA
y_{2t} : Log GDP EURO-area

Figure 30 shows components of the bivariate model.

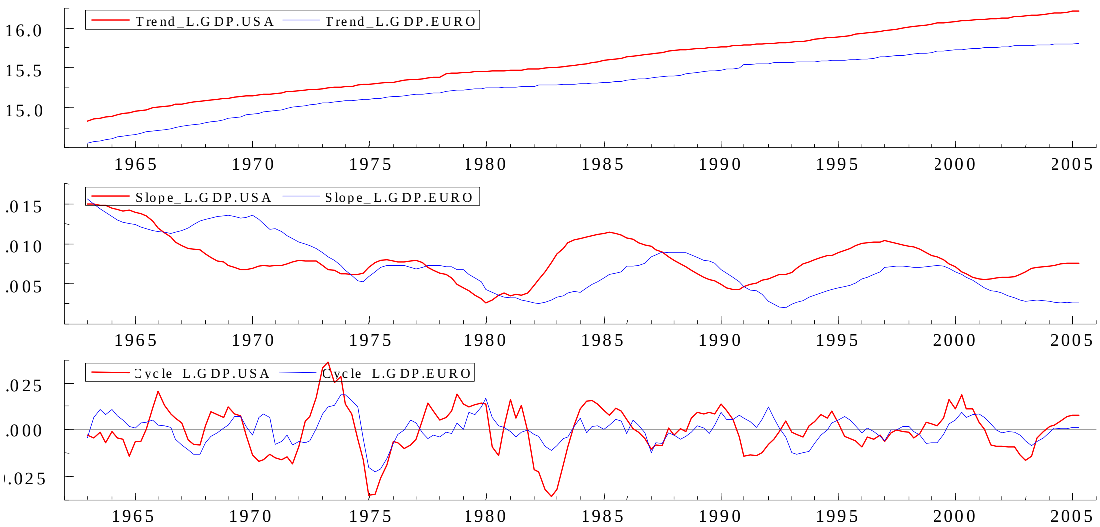

Figure 30. Components graph from the bivariate model, USA and Euro-area

We don't constrain the model to have any common components, thus the trends, slopes and cycles are not constrained for any common features between two series. However, from the slope component graph, we see that the long-term growth (slope) of the Euro-area GDP follows the USA GDP growth with few years delay. STAMP reports 0.27272 for the slope disturbance correlation. The slope graph shows co-movement of the two series. But it is not clear to conclude that the long-term growth of the USA GDP is the main reason for the development of the Euro-area GDP long-term growth. Especially, the few years of lagging relationship is too long to accept that the Euro-area GDP is following the USA GDP. However, this long-term related correlation generated by STM may be an interesting part to explore for next study.

The cyclical movements tell us the short-term correlation of the two series. STAMP reports 0.31869 for the cycle disturbance correlation. The similar cycles are generated with same damping factor and frequency. The estimated cycles' length is 5.16078 ('years'). From the cycle graph, we observe that the USA cycle is leading the Euro-area cycle in most of the time. It is clear from the mid 90's. At this point, it may be interesting to examine the meaning of a cyclical correlation. By definition, cycles represent the short-term fluctuation of an economy. According to New Keynesian Theory, a short-term means that the price remains unchanged, thus the economy will fluctuate when the economy is hit by shocks. This is why different economies can be correlated in their short-term movements when a global shock occurs. Furthermore, the USA economy is the world's largest, which can influence greatly on other economies.

For better investigation of the lagged relationship between the USA and Euro-area economy, we find out the cycle correlation of Euro-area against the USA cycle. Figure 31 shows the cycle correlation.

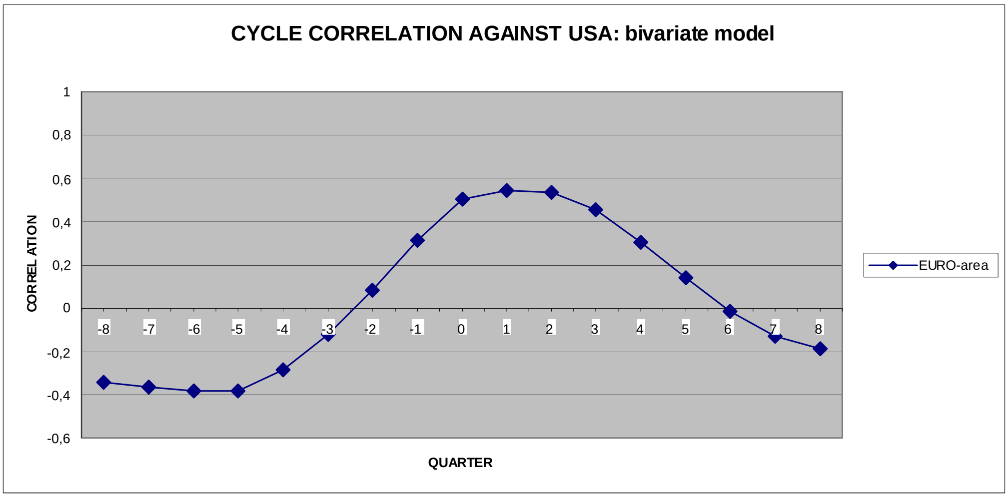

Figure 31. Correlation of the Euro-area cycle against the USA cycle

We see from the graph that the Euro-area cycle follows the USA cycle after one quarter, with correlation of 0.5432. When we recall the result of the multivariate model in section 2.3, the cycle correlation between Euro-area and USA is almost unity without any delay, which is quite different from the bivariate model. As we distinguish the global shock from the country-specific shock, it is more reasonable to believe the bivariate model generate more appropriate cyclical correlation for the Euro-area and the USA GDP time series than the multivariate model does.

3.4.2 Bivariate GDP structural time series model, USA and GBR

The model is

$\boldsymbol{y}_t$ = Trend + 1 Cycle(s) + Interventions + Irregular

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} 16.223 \\ 15.807 \end{pmatrix} \boldsymbol{\mu}_{t-1} + \begin{pmatrix} 0.0081 \\ 0.0033 \end{pmatrix} \boldsymbol{\beta}_{t-1} + \begin{pmatrix} 0.007 \\ 0.008 \end{pmatrix} \boldsymbol{\psi}_t + \begin{pmatrix} 0.012\text{Irr}1970.4 + 0.032\text{Lev}1978.2 \\ 0.046\text{Lev}1973.1 - 0.024\text{Irr}1974.1 + 0.029\text{Irr}1979.2 \end{pmatrix} + \boldsymbol{\eta}_t + \boldsymbol{\varepsilon}_t$$

y_{1t} : Log GDP USA
y_{2t} : Log GDP GBR

Figure 32 shows components of the bivariate model.

It is noticeable that the disturbance correlation of the slope component reported by STAMP is 0.99375. it is almost close to unity, which means a perfect correlation. In this instance, we may generate a common trend by restricting the rank of the slope disturbance covariance matrix to be unity. A common trend will lead the two series to have same long-term growth, and the other components will be generated under the assumption of a common trend. However, the main concern of this thesis is to find out the cyclical correlation of the series, and generating a common trend will cause different cyclical movements[3].

[3] Actually, when we generate a common trend for the USA and GBR GDP time series, the estimated cycle's length is 249.975 ('years'), which is not interpretable. A possible reason may be that forcing the slope disturbance covariance to have a linear combination will make the system loose the control over the cyclical movement. In other words, the trend will be deterministic in its own way. Thus, the common trend and the common (similar) cycle need to be handled separately in our GDP time series case. As a result, we will concentrate on the similar cycle of the bivariate model.

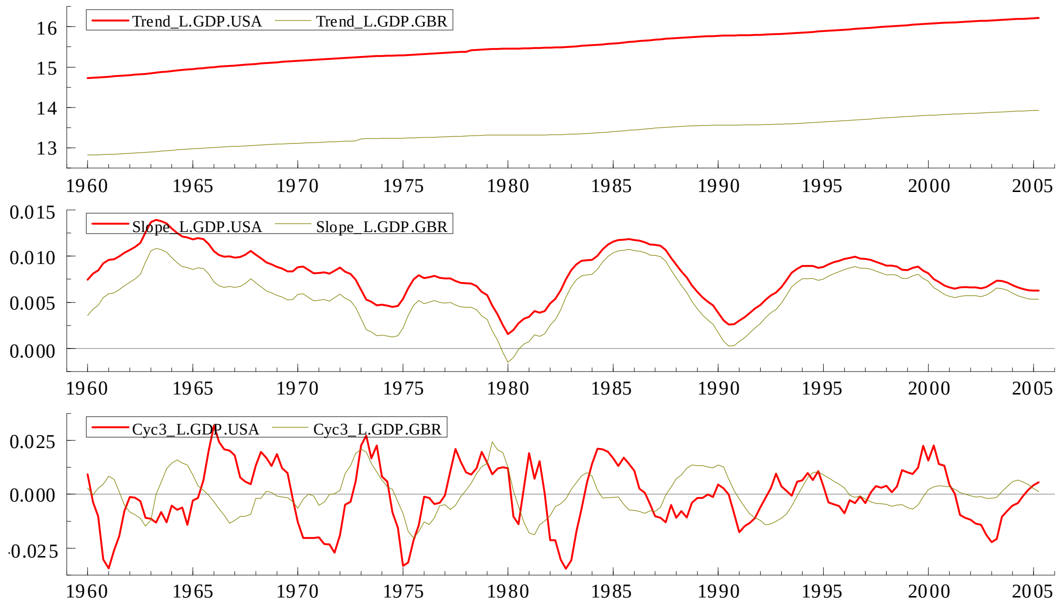

Figure 32. Components graph from the bivariate model, USA and GBR

From the cyclical component graph, we can notice that the cycle correlation of the two series is not higher than one we observed from the USA/Euro-area bivariate model. STAMP reports the cycle disturbance correlation with 0.10769 and the length with 6.00867 ('years'). The USA cycle is leading the GBR cycle in the mid 70's and 90's, except the 80's. This can cause difficulties to figure out the lagging/leading relationships of the two series over the periods.

However, we follow the same procedure as the USA/Euro-area case to find out the correlation of the two series.

Figure 33 shows the cycle correlation between the GBR and USA cycle.

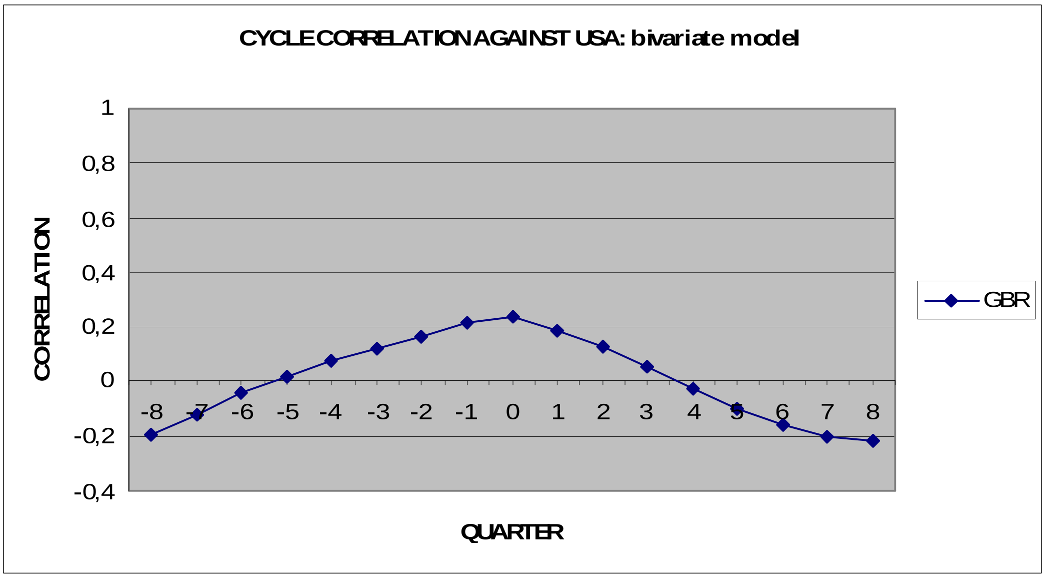

Figure 33. Correlation of the GBR cycle against the USA cycle

Figure 33 tells us that the GBR cycle and USA cycle have correlation around 0.24, and there is no lagging/leading relationship between the GBR cycle and the USA cycle. When we again examine the similar cycles in figure 32, we can notice the reason for this no lagging/leading relationship. It is not because the GBR and USA cycle is moving at the same time, but because the different outcomes through different time line. Before the mid 70's and 80's, it seems that the GBR cycle leads the USA cycle and most of the other periods seems the other way. How can we handle this problem? The GBR economy has its own reputation to behave differently from any other countries. Krolzig (2000), Monfort *et* al (2002) and Artis (2003) regard the GBR economy as a special case, since, it doesn't fit to models that other countries do. This special character that GBR has, may cause the problem. The best way that we can do with our statistic program, STAMP, is to shorten the sample period and follow the same procedure as before. This will be done with all the other areas when we compare our result with the one by Benedictow and Johansen (2005).

We have to remember how sensitive a time series model can be, as we have just observed from the GBR/USA GDP bivariate model. This is not only for the STAMP users, but also all empirical methods users. We have to be careful for the selection of variables and periods. Appropriate tests of the model have to be done to reduce possible failures.

3.4.3 Bivariate GDP structural time series model, USA and Sweden

The estimated model is

$\boldsymbol{y}_t$ = Trend + 1 Cycle(s) + Interventions + Irregular

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} 16.213 \\ 14.696 \end{pmatrix} \boldsymbol{\mu}_{t-1} + \begin{pmatrix} 0.007 \\ 0.006 \end{pmatrix} \boldsymbol{\beta}_{t-1} + \begin{pmatrix} 0.008 \\ 0.002 \end{pmatrix} \boldsymbol{\psi}_t + \begin{pmatrix} -0.017\mathrm{Irr}1970.4 + 0.031\mathrm{Lev}1978.2 \\ 0.0239\mathrm{Irr}1980.1 - 0.029\mathrm{Irr}1980.2 \end{pmatrix} + \boldsymbol{\eta}_t + \boldsymbol{\varepsilon}_t$$

y_{1t} : Log GDP USA
y_{2t} : Log GDP Sweden

Figure 34 shows components of the bivariate model.

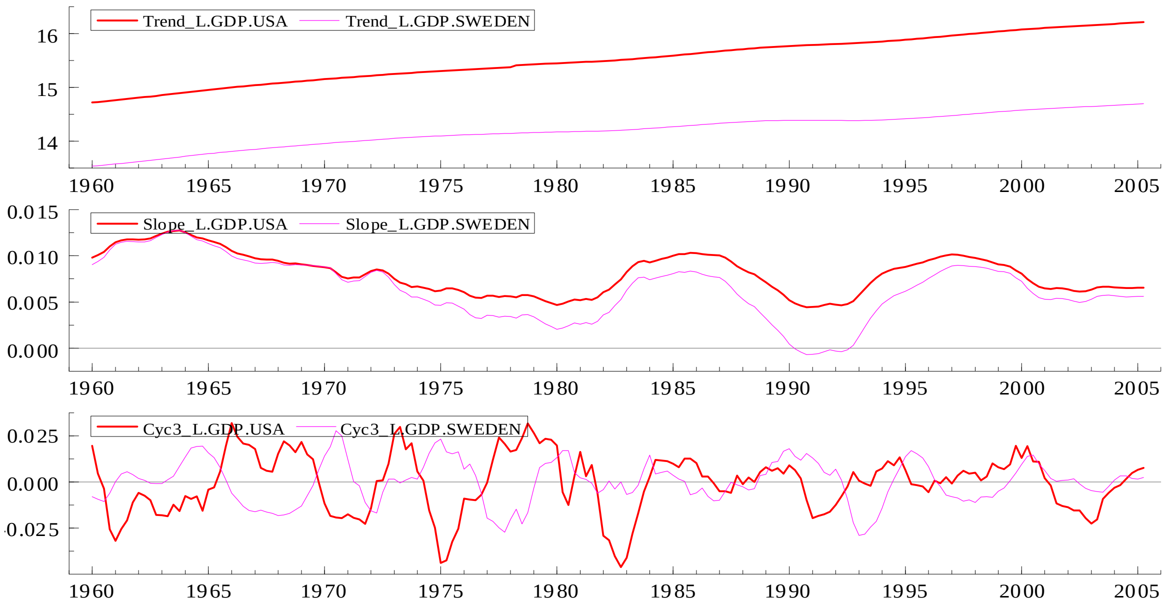

Figure 34. Components graph from the bivariate model, USA and Sweden

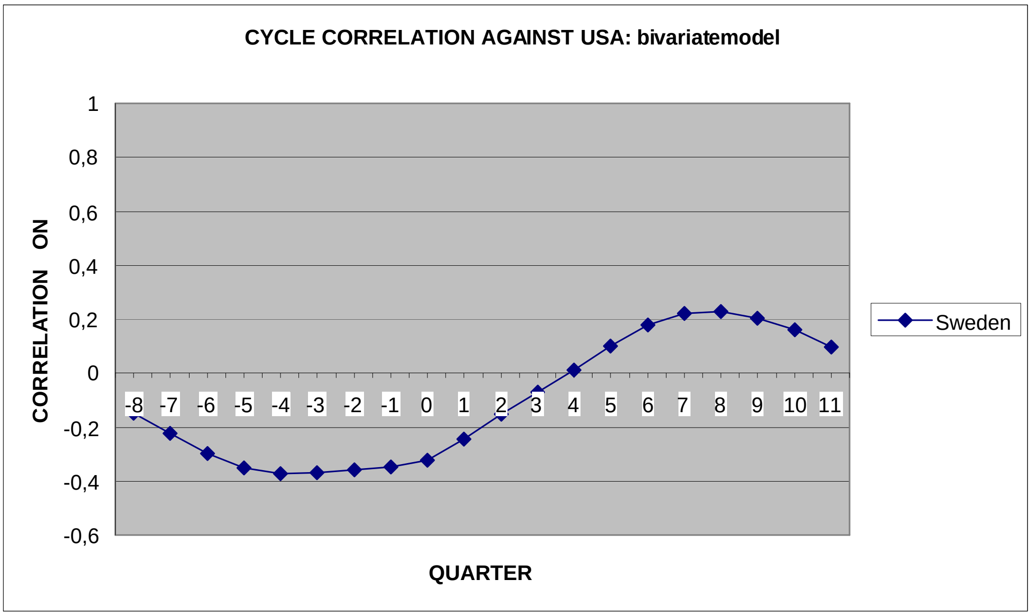

Figure 35. Correlation of the Swedish cycle against the USA cycle

Figure 35 tells us that the Swedish cycle is lagging the USA cycle by two years. The estimated correlation is 0.23. According to Benedictow and Johansen (2005), the Swedish cycle is lagging the USA cycle by 6 quarters with correlation around 0.5. The change of correlation pattern caused by the exchange rate regime change and the Swedish economy crisis during the early 90’s may be possible reasons for the low correlation estimated by STAMP. As we noticed earlier, the estimated lagging/leading correlation may be quite different when we have series like Sweden and USA. The cyclical correlation has changed over time, and the size (length) of the time series may mislead overall correlation of the series because of it. We will draw a similar graph as figure 35 later with data from 1971.1 to compare with Benedictow and Johansen (2005). It is assumed to generate different correlation, since the data is shorter than the result above. How big (long) should the time series be to generate appropriate result, which tells us a reasonable cyclical correlation between two nations? This may be one of the most important questions we should answer in advance, and the answer will vary from series to series.

3.4.4 Bivariate GDP structural time series model, USA and Japan

The model is

$\boldsymbol{y}_t$ = Trend + 1 Cycle(s) + Interventions + Irregular

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} 16.215 \\ 20.111 \end{pmatrix} \boldsymbol{\mu}_{t-1} + \begin{pmatrix} 0.008 \\ 0.006 \end{pmatrix} \boldsymbol{\beta}_{t-1} + \begin{pmatrix} 0.006 \\ 0.004 \end{pmatrix} \boldsymbol{\psi}_t + \begin{pmatrix} -0.018\text{Irr}1970.4 + 0.033\text{Lev}1978.2 \\ 0.023\text{Irr}1968.4 - 0.044\text{Lev}1974.1 \end{pmatrix} + \boldsymbol{\eta}_t + \boldsymbol{\varepsilon}_t$$

y_{1t} : Log GDP USA
y_{2t} : Log GDP Japan

Figure 36 shows components of the bivariate model.

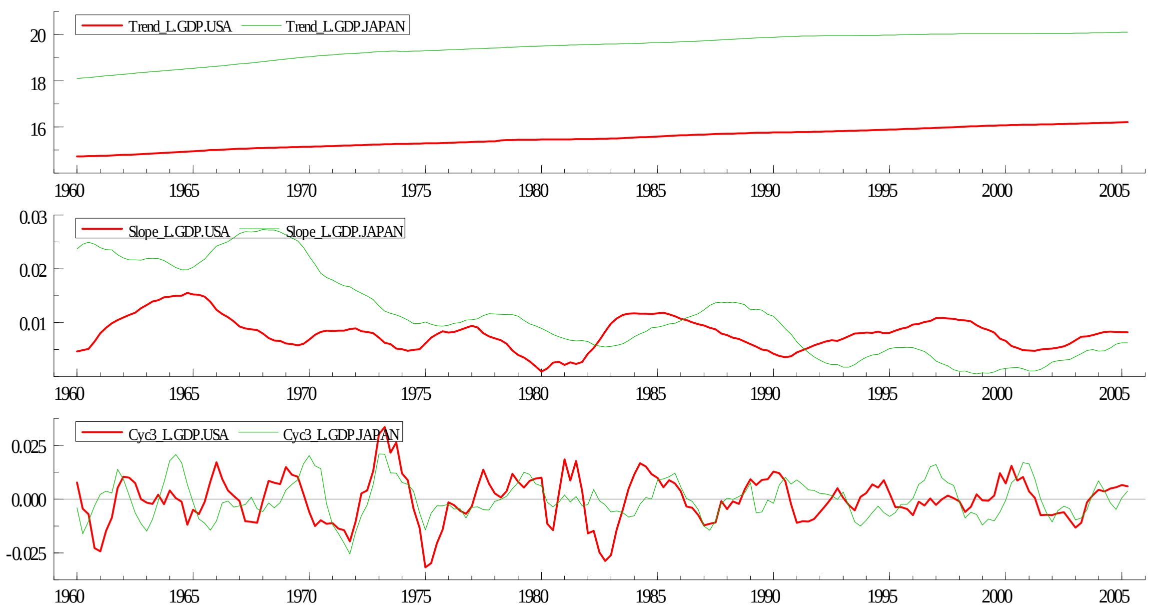

Figure 36. Components graph from the bivariate model, USA and Japan

The slope disturbance correlation between the USA and the Japanese GDP is -0.12128. It indicates that there is almost no correlation in the long-term growth or in other words, the trend component between these two countries. This is quite different from the GBR and Swedish cases, which show the slope disturbance correlation being close to unity. The result between USA and EURO-area shows much lower correlation for the slope disturbance with 0.273, which is also hard to generate a common trend. The size of the economy may be a possible reason for this. The EU economy is world's second largest economy after USA and the Japanese economy is the fourth larest after USA, EU and China (CIA, 2006). When the size of economy is big enough to maintain its own system like EU and Japan, the correlation of the trends with USA should not be close to unity. In addition, the geographical distance (independence) of the Japanese economy may also be a possible reason for the low correlation. Japanese economy experienced a strong and stable growth through the 60's, 70's and 80's until the economic crisis in the 90's. The oil shocks in 70's were less painful than other countries. The Japanese economy has its own unique characteristics, and this may cause the low correlation of the slope disturbance, hence, the long-term growth.

The cycle disturbance seems to be correlated according to the graph above. Especially, from the mid 70's, the similar cycles moving closely. Figure 37 shows the lagging/leading relationship between the two cycles.

The Japanese cycle is lagging the USA cycle by 3 quarters with correlation around 0.35. The lagging relationship is assumed to be shorter in the next chapter, where we compare the cyclical correlations from our model to Andreas and Johansen (2005). Since we build the model from 1971.1, the effect of the 60's longer lagging term will be removed, giving more appropriate result.

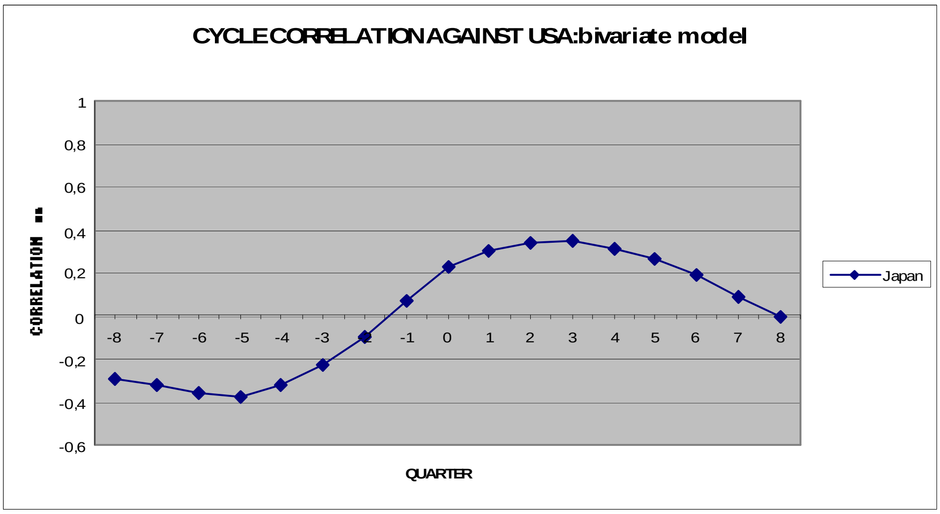

Figure 37. Correlation of the Japanese cycle against the USA cycle

3.4.5 Bivariate GDP time series model from 1971.1

In section 2.4.1-2.4.4, we have seen the cyclical correlations of Euro-area, GBR, Sweden and Japan with USA from 1960 to 2005. Now we compare our result to Benedictow and Johansen (2005) in this chapter. For more correct comparison, we use data for same period, from 1971 to 2005. Figure 38 shows the lagging/leading relationship between cycles.

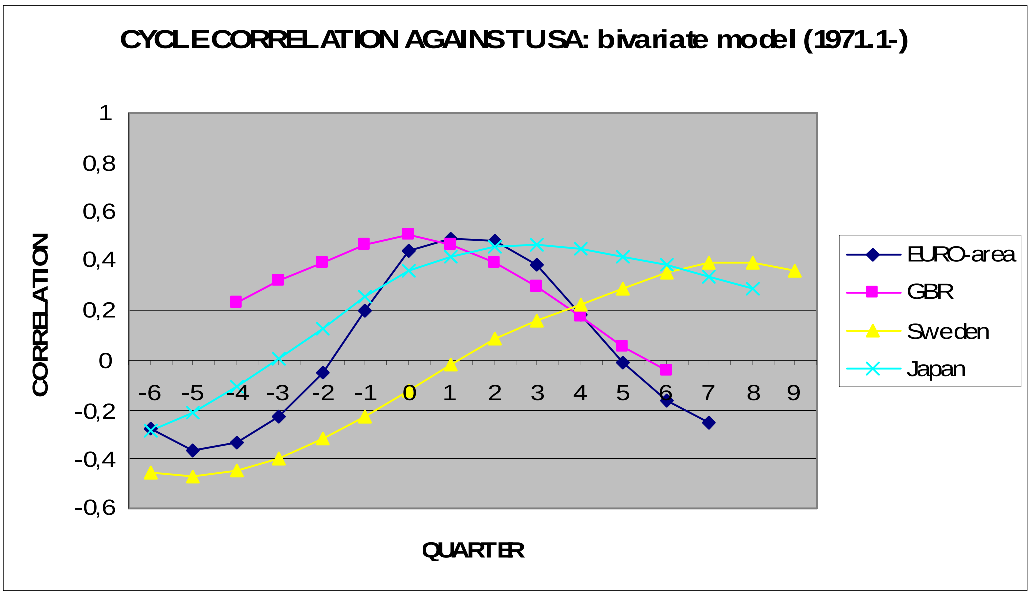

Figure 38. Cycle correlations against USA cycle

When we recall Benedictow and Johansen (2005), the EURO-area cycle is lagging by 2 quarters with correlation around 0.75, and the GBR is no lagging with correlation around 0.75. The Swedish cycle shows 6 quarters lagging with correlation 0.5. In our model, the Euro-area cycle is lagging by a quarter with correlation 0.49, and the GBR is no lagging with correlation 0.51. The Swedish cycle shows 8 quarters lagging with correlation 0.4. The Japanese cycle shows 3 quarters lagging with correlation 0.46. The cycle correlations are similar to the HP-filtered cycles, except the size of the correlation. It seems to have smaller correlations with STM than HP-filter. A possible reason may be the structure of STM, which decomposes a time series into different components (level, slope, trend, irregular and possibly seasonal). When we use a HP-filter for decomposing time series, the cycle may include the irregular disturbance into the cyclical disturbance, and this may cause the cycle correlation to be greater than its actual value. It is also difficult to distinguish between long-term and short-term movements of a model, when we apply a HP-filter. On the other hand, a STM will exclude the irregular disturbance from the cyclical disturbance, giving more credible value for the correlation. The lagging/leading relationships in figure 38 are almost identical to the Benedictow and Johansen (2005). We see that a STM gives similar result as HP-filter. With its simplicity and direct interpretation, it is convincing to use STM for generating business cycles. But we have to remember the sensitivity of the model all the time.

4. Conclusion

From the thesis, we find out that constraining the trend to be stochastic will vary the outcomes of the cycle. This will lead the forecast to vary as well. Questions of how stochastic a trend should be will depend on variables, lengths of series, and the purpose of the study. If the trend is so stochastic that it matches almost to the actual series, the cycle will have very small disturbance variance. As a result, the model's forecast will be poor. If the trend is not stochastic such as a deterministic trend, the model may forecast well, but shows very poor performance on the actual series. The use of interventions affects greatly on the trend's flexibility. With and without interventions give different trend and cycles. However, we find out that for the GDP time series, it is sometimes difficult to identify the background of an intervention. We witness this with the USA, and GBR GDP time series. Consequently, we have to balance between the trend and the cycle with solid theoretical background.

We have studied the forecasts of each univariate model. In STM, we obtain each components' forecasts separately, and they are directly interpretable. However, it may lead us to misunderstand the forecasts, if we only look into the cycle forecast. The STM forecasts both trend and cycle, thus we should refer both trend and cycle for forecasting. For doing this, we suggest to use the forecasted growth rate. This will shows the sum growth rates of both trend and cycle.

The outcome of the multivariate modeling shows somewhat incorrect cycle correlations, which says the GBR cycle lead the USA cycle and the Japanese cycle doesn't have any correlation with the USA cycle. It is not clear why it gives such result. In the thesis, we try to find possible reasons for that. Further studies should be made for this. The alternatively built bivariate models show proper results, which can be reasonably compared with Benedictow and Johansen (2005). However, the bivariate models are too sensitive to produce general factors on the model. If we change the length of the series, or interventions, or other features of the model a little bit, the outcome will be fairly different. It is recommended to aware fully about the models and the variables before using the program, STAMP.

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